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FEASIBILITY STUDY FOR DESIGN OF A
BIOCYBERNETIC COMMUNICATION SYSTEM

Lawrence R. Pinneo, et al

Stanford Research Institute

Prepared for:

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March 1973

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FEASIBILITY STUDY FOR DESIGN OF A BIOCYBERNETIC COMMUNICATION SYSTEM

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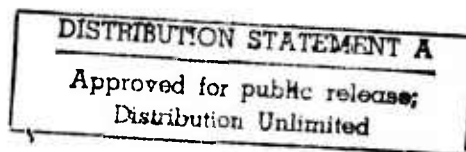
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SUMMARY

The objective of this research is to test the feasibility of designing a close-coupled, two-way communication link between man and computer using biological information. The research plan is to conduct experiments to determine whether biological information from the central nervous system and muscles of portions of the vocal apparatus can be directly related to thought processes; whether this information can be recognized by a computer; and whether the biological processes (representing a particular thought) can be induced in a human user. Should such a close-coupling between man and machine prove to be feasible, an individual using such a biocybernetic communication system would be able to "talk" (i.e., both send and receive) with a computer at the speed of thought, rather than be limited by the speed of a teletype or other electromechanical device through which ideas in the form of questions and answers must normally pass.

The research plan was predicated on existing evidence that verbal ideas or thinking are subvocally represented in the facial muscles of the vocal apparatus (see Introduction, p. 4, for details). If the patterns of this muscle activity are at all similar to those involved in normal overt speech, then it is reasonable to assume that the electrical activity of the brain during covert speech (verbal thinking) may be similar to that during overt speech. The objective of the first year of research was to establish the validity of this basic premise.

The general methodology was to record the electromyograph (EMG) of facial muscles involved in speech from volunteer human subjects during performance of language tasks. The electroencephalograph (EEG) from scalp electrodes overlying areas of the cerebral cortex involved in speech was recorded simultaneously (see Methods, p. 7, for details). The resulting analog data were then digitized for computer processing, and several statistics that reveal patterns of cortical activity were calculated. These statistics were then used in a computer pattern recognition program designed to identify features in the physiological data associated with specific words, whether overtly or covertly produced.

This report describes results of computer analysis of EMG and EEG recordings from each of three subjects during performance of a language task on two separate occasions. The purpose was to determine whether the computer could correctly classify 15 overtly spoken English words based on the EMG and EEG electrophysiological patterns alone. Several statistics were later applied to the EMG and EEG responses that were coincident with the 15 word utterances (each repeated ten times at each of the two sessions), but only one statistic was found useful for successful pattern recognition. This was based on calculating an average response

for each electrode for the period three seconds before and three seconds after the onset of vocalization of a word. Each of the 15 average responses per electrode (six electrodes, or 90 average responses for the 15 words per subject per session) then served as a template against which individual responses were compared. These comparisons were made by calculating the RMS (root-mean-square) difference between a single response of each electrode and the 15 word templates for that electrode. The individual electrode response was then classified as the word for that template with which the RMS difference was a minimum (see the Appendix for details of mathematics).

The significant results were:

- (1) Both EMG and EEG responses, taken separately or together, were used to classify any one or all of the 15 overtly spoken words. The percentage of correct classifications for all electrodes of the three subjects for two sessions each ranged from 9% to 84%.
- (2) Out of 900 possible correct classifications across all subjects and sessions, 74% of the words were correctly classified by EMG responses alone, 63% by EMG plus all EEG responses, and 34% by EEG responses alone (see Table 6, p. 34, for details). Chi square tests of significance showed that these correct classifications could have occurred by chance with a probability of less than 1 in 1000.
- (3) Reliability within each subject from one session to the other was high. Templates for one session of a given subject could serve to correctly classify words based on EMG and EEG responses of the other session nearly as well as templates within a session. In addition, a higher rate of correct classifications was made on the second session for all three subjects than on the first, indicating a learning or habituation effect that lowered response variability.
- (4) When templates of one subject were used to classify words based on individual responses of another subject, the percentage of correct classifications for EEG responses was no greater than chance expectation. The percentage of correct classifications for EMG was greater than chance, but not nearly so good as within subjects. Thus, it appears that each subject's biological patterns associated with speech are unique.
- (5) Six possible sources of error in word classification were identified, and their relative contribution to decreased success was evaluated. It was determined that if all sources of error could be eliminated, significant gains in correct word classification using biological responses would be achieved (perhaps approaching 90% or better).

We conclude that it is feasible for a human verbally to communicate overtly with a computer using biological information alone, with a high degree of accuracy and reliability, at least with a small vocabulary. During the next year attempts will be made to eliminate all sources of error, to determine the optimum locations for EEG recording, and to communicate (i.e., recognize signals) with the computer during silent speech (verbal thinking) using biological information alone.

INTRODUCTION

Our approach is predicated on previous research conducted by the authors and others in the areas of psychophysiological measures of thought, computer processing of electrophysiological information, and development of computer pattern recognition techniques. This research is summarized below (see SRI Proposal LSU 71-145, dated 10 December 1971, for details).

Early work by Watson (1930) indicated that verbal cognitive processes may be represented in muscle activity of the vocal apparatus as subvocal speech. McGuigan (1970), reviewing studies of such covert oral behavior during the silent performance of a language task, concluded that covert oral behavior (as measured by the electromyograph, or EMG) increases significantly in amount and frequency of occurrence, compared with when the subject is not performing a silent language task. Thus, verbal ideas, or thinking, although unquestionably a central nervous system process (MacNeilage and MacNeilage, 1971), has some sort of peripheral representation in the muscles of the vocal apparatus.

If the patterns of this muscle activity are at all similar to those involved in normal overt speech, then it is reasonable to assume that the electrical activity of the brain during covert speech, or thinking, may be similar to that during overt speech. That is, a measure of the scalp-recorded electroencephalograph (EEG) of a human during verbal thinking should be similar to the EEG of the same individual when expressing the same thoughts vocally.

However, previous examination of the "raw" EEG has not revealed any obvious pattern related to overt or covert speech; it may be that only patterns of EEG activity between various areas of the brain at a given moment are related to speech. Several technical advances made in recent years have provided us with some tools to deal with this possibility. Most important is the use of computer techniques for frequency analysis of the real-time EEG and the development of multivariate statistical procedures (Donchin and Lindsley, 1966; John et al., 1964; and Rose and Lindsley, 1965). These procedures allow comparison of specific components of EEG waveforms that are known to reflect different neurophysiological processes. In addition, certain statistics, such as auto- and cross-spectral frequency analysis (Walter, 1963; Walter and Adey, 1965), the linear coherence function (Adey, Kado, and Walter, 1967), and the weighted-average coherence (Galbraith, 1967), may be used to determine the degree of interaction between two different brain regions. Thus, with these tools, the EEG waveforms from several areas of the brain that are neurophysiologically related to speech may be examined to determine whether their patterns of interaction are similar during overt speech and verbal thinking.

A thorough visual analysis of the statistical results of these EEG waveforms would be extremely complicated and time-consuming. Therefore, we have turned to machine pattern recognition techniques to analyze the patterns of the EEG interrelationships to be found in the average responses, cross-spectra, and coherence functions related to covert and overt speech. Most useful for this feasibility study are techniques for on-line pattern recognition (Hall *et al.*, 1968). These techniques allow the user to process multivariate data by using all reasonably conceivable graphic plots, and manipulate the data further using appropriate numeric procedures available in the computer system. Thus, for our purposes, a set of statistics such as the average responses, coherence functions of the EEG, the patterns of the EMG changes with overt speech, and other measures may be plotted as a function of each other for specific covert language tasks (i.e., thinking).

The objective of the first year of this feasibility study was to establish the validity of the basic premise that patterns of biological information can be related to language behavior. This has been accomplished by:

- (1) Measurement of EMGs of the vocal apparatus and EEGs overlying cerebral areas involved in speech during overt and covert language tasks.
- (2) Computer processing and analysis of the averaged biological activity, the cross- and auto-spectra, coherence, and weighted-average coherence of the EEG and EMG as related to speech.
- (3) Application of computer pattern recognition techniques to determine if the statistical patterns of biological activity from the EMGs and EEGs are similar during overt and covert speech, and to attempt to machine-identify silent language performance with the best pattern recognition method.

During the first year two experiments were conducted, designated Group I and Group II. A complete description of the methods and results for Group I data and preliminary results for Group II data were given in the First Semi-Annual Technical Progress Report, dated October 1972. This report describes details of the computer analyses of Group II data. To place the Group II results in perspective, a summary of the results from Group I follows.

In the first experiment (Group I data), EMG and EEG records were obtained during performance of a language task under various conditions of stimulus presentation, including: visual presentation, overt response; visual presentation, covert response (silent reading); auditory presentation, eyes open, overt response; and auditory presentation, eyes closed, overt response. (The last two conditions were chosen because the EEG is characteristically different when the eyes are open compared with closed.) The language task, recommended by a psychophysiological linguist consultant, consisted of words and sentences most likely to reveal

patterns in the EMG during speech. In the second experiment (Group II data), similar records were obtained, but under slightly different stimulus conditions and with 20 repetitions per subject for reliability tests. These conditions included visual presentation with overt response of five selected monosyllabic words, and five bisyllabic words, with the accent on the first syllable and then on the second (to compare effects caused by ordering the emphasis), for a total of 15 words.

Significant results of the Group I data and preliminary analysis of the Group II data were:

- (1) EMG patterns for each word were specific for that word.
- (2) EMG patterns for a given word were consistent, showing less within subject variability than between subject variability.
- (3) Averaged EMG patterns for a given word spoken by a given individual were sufficiently consistent for that averaged EMG to serve as a template for identifying the same word when it was imbedded in a sentence.
- (4) There was some variability in EMG patterns for bisyllabic words between accent on the first or second syllable, but it was sufficiently small so that either pattern could be used visually to identify the same unaccented word imbedded in a sentence.
- (5) The pattern recognition analysis carried out on the Group I data distinguished words beginning with "H" from all other words.

Thus, the results from Group I data and the results from Group II data before computer analysis showed that the EMG may be used to identify specific overtly spoken words of a given individual. The results also implied that patterns of EEG activity associated with these words may be used to identify the same word when covertly produced (as in verbal thinking).

METHODS FOR GROUP II EXPERIMENT

Subjects

Subjects were three adult, right-handed, human female volunteers, ages 21-41, hereinafter designated B, C, and D. A total of six experimental sessions, each of about 2½ hours duration, were all carried out using the same experimental paradigm. A given session for a given S is identified by the S's letter code and her chronological session; thus C5 was the fifth experimental session for subject C. Before conducting these sessions, several apparatus debugging sessions were carried out with a fourth S, A.

Apparatus

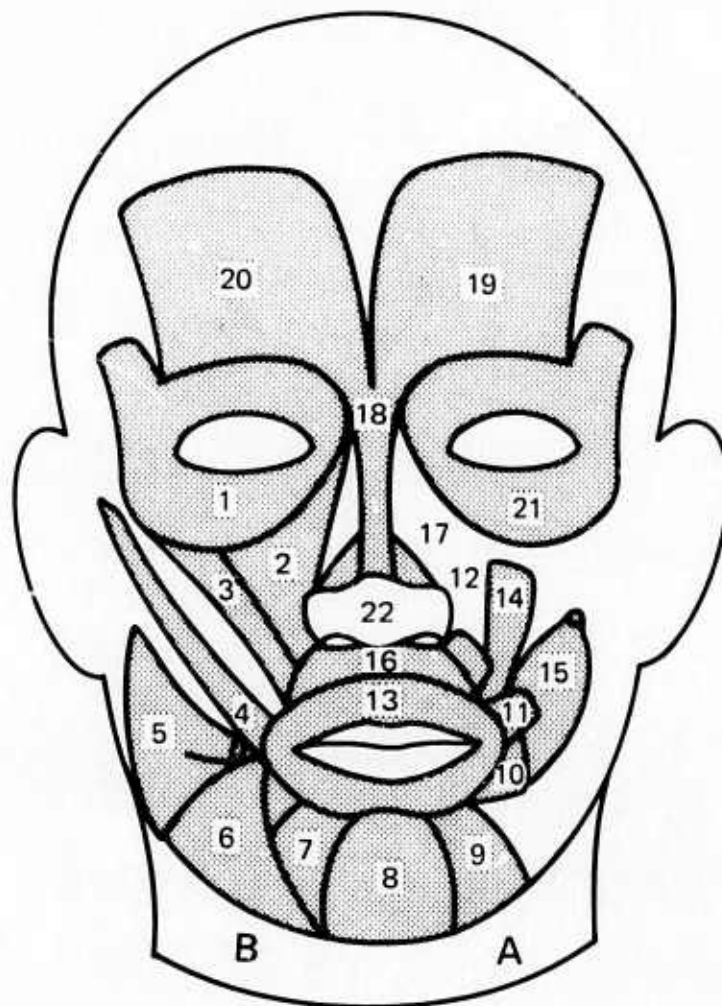
Electrodes and Electrode Placements

For surface recording of the EMG from facial muscles involved in speech production, Beckman silver, silver-chloride miniature disk skin electrodes (2-mm exposed) were used. EEG scalp electrodes, reference electrodes, and the ground electrode were Beckman silver, silver-chloride standard disk skin electrodes (8-mm exposed). Two reference sites were employed--the skin under the left mastoid for EMG recordings and the skin under the right mastoid for EEG recordings. All recordings were monopolar to record absolute potentials at the recording site.

Selected skin areas were first cleaned with acetone (alcohol on the face), then conditioned with Redox electrode paste by rubbing it into the skin, and followed by a second cleaning with acetone. A conductive, paste-filled electrode was then placed over each recording area and attached by a sticky collar to the underlying skin. Following a recording session, electrodes were removed, and the skin was cleaned with acetone or alcohol.

Figure 1 shows the facial musculature. Muscles involved in vocalization that are surface-recordable are 2, 3, 4, 6, 7, 8, 9, 10, 11, 13, and 16. Each of these locations was tested during preliminary experiments. In Experiment 1, combined sites 13/16 and 7/8 were found to produce the most reliable integrated EMG patterns during overt speech and so were used for collecting Group II data.

Figure 2 illustrates the 10/20 system of EEG recording (Penfield and Jasper, 1954). Locations F7, anterior C5, T5 and T6 were used for Group II. Three of these placements overlie areas thought to be involved in speech (Penfield and Roberts, 1959), as follows: F7, Broca's



- | | | |
|--|---|---------------------------------|
| 1. Orbicularis oculi m. (right) | 8. Mentalis m. | 15. Buccinator m. (left) |
| 2. Quadratus labii superioris m. (right) | 9. Quadratus labii inferioris m. (left) | 16. Depressor septi nasi m. |
| 3. Zygomatic head of quadratus labii superioris m. (right) | 10. Triangularis m. (left, cut) | 17. Nasalis m. (left) |
| 4. Zygomaticus m. (right) | 11. Zygomaticus m. (left, cut) | 18. Procerus m. |
| 5. Risorius m. (right, cut) | 12. Quadratus labii superioris m. (left, cut) | 19. Frontalis m. (left) |
| 6. Triangularis m. (right) | 13. Orbicularis oris m. | 20. Frontalis m. (right) |
| 7. Quadratus labii inferioris m. (right) | 14. Caninus m. (left) | 21. Orbicularis oculi m. (left) |
| | | 22. Nasalis m. (right) |

FIGURE 1 MUSCLES OF THE FACE (AFTER VAN RIPER AND IRWIN, 1958)

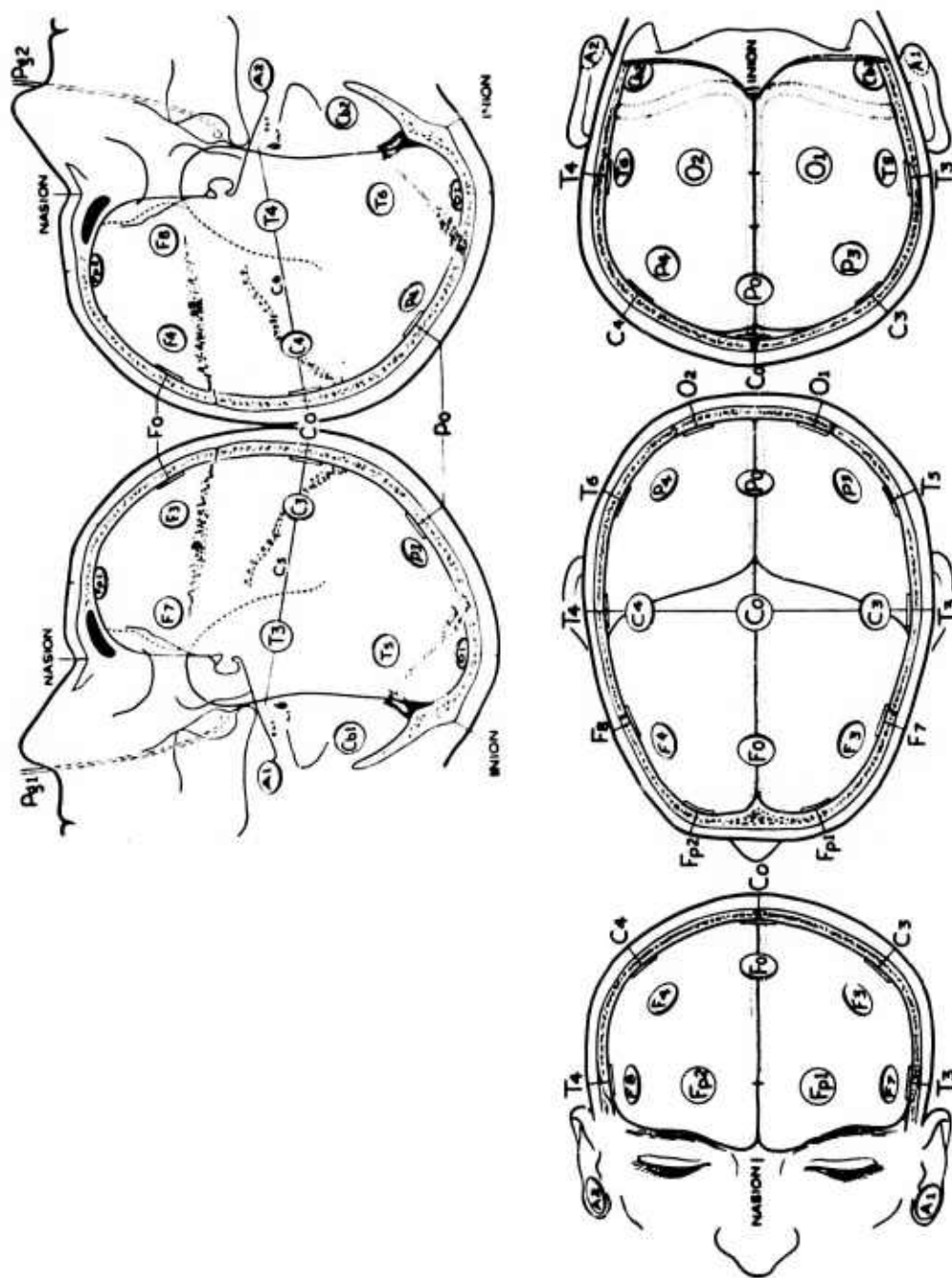


FIGURE 2 ELECTRODE PLACEMENTS FOR 10/20 METHOD OF EEG RECORDING
(AFTER PENFIELD AND JASPER, 1954)

speech area; anterior C5, motor control of vocal musculature; and T5, Wierneki's area for speech organization and comprehension. In addition, location T6 on the right (nondominant) hemisphere, the homologue of T5 over the dominant hemisphere, was employed as a control.

After electrodes were attached, Ss were seated in a semi-dark, electrically shielded booth. All electrodes were plugged into a junction box leading to the recording equipment. Electrode resistances were checked; if any one electrode was found to be greater than 5000 ohms, it was removed, the skin further cleaned and conditioned, and the electrode replaced. When all electrodes checked correctly, the S was instructed in the experimental procedure, a microphone for recording speech as placed in front of the S's mouth, and the recording session begun.

Equipment

Figure 3 shows a diagram of the equipment setup. Electrodes from the facial musculature were led first to a Beckman Model 9852A EMG integrator coupler, with a fixed time constant of 0.25 sec, and pass band of 20 to 5000 Hz. For Group II, channels 1 and 2 of the Dynograph were used to record the integrated EMG. EEG electrodes were led to Beckman type 9806A couplers, within the pass band set to 2 to 22 Hz. flat; channels 3, 4, 5, and 6 recorded the instantaneous EEG. Channel 7 recorded the voice output of the microphone; channel 8 was not used. Amplitude normalization was carried out by setting all like channels (EMG or EEG) to the same gain.

All physiological signals were preamplified by Beckman Model 481B preamplifiers, and were then led in parallel to Beckman Model 482A power amplifiers with calibrated zero suppression and to an Ampex SP-300, seven-channel, analog instrument tape recorder. The output of the Beckman power amplifiers drove ink-writing galvanometers on chart paper moving at 25 mm/sec. The output on the chart paper could be set by a switch to record either the input to the Ampex tape recorder (i.e., "direct" recording) or the output of the Ampex; this feature enables the investigator to calibrate and monitor the permanent tape recording. EMG and EEG recordings were on channels 1 through 6 of the Ampex, using frequency modulation, at 1-7/8 in./sec (pass band dc-312 Hz.); voice was recorded on channel 7.

Group II data filled one 10- $\frac{1}{2}$ -in. Ampex tape with analog data. These data were then sent through the data analysis system using the Linc-8 laboratory instrument computer and a CDC-6400 computer (see Data Analysis section below).

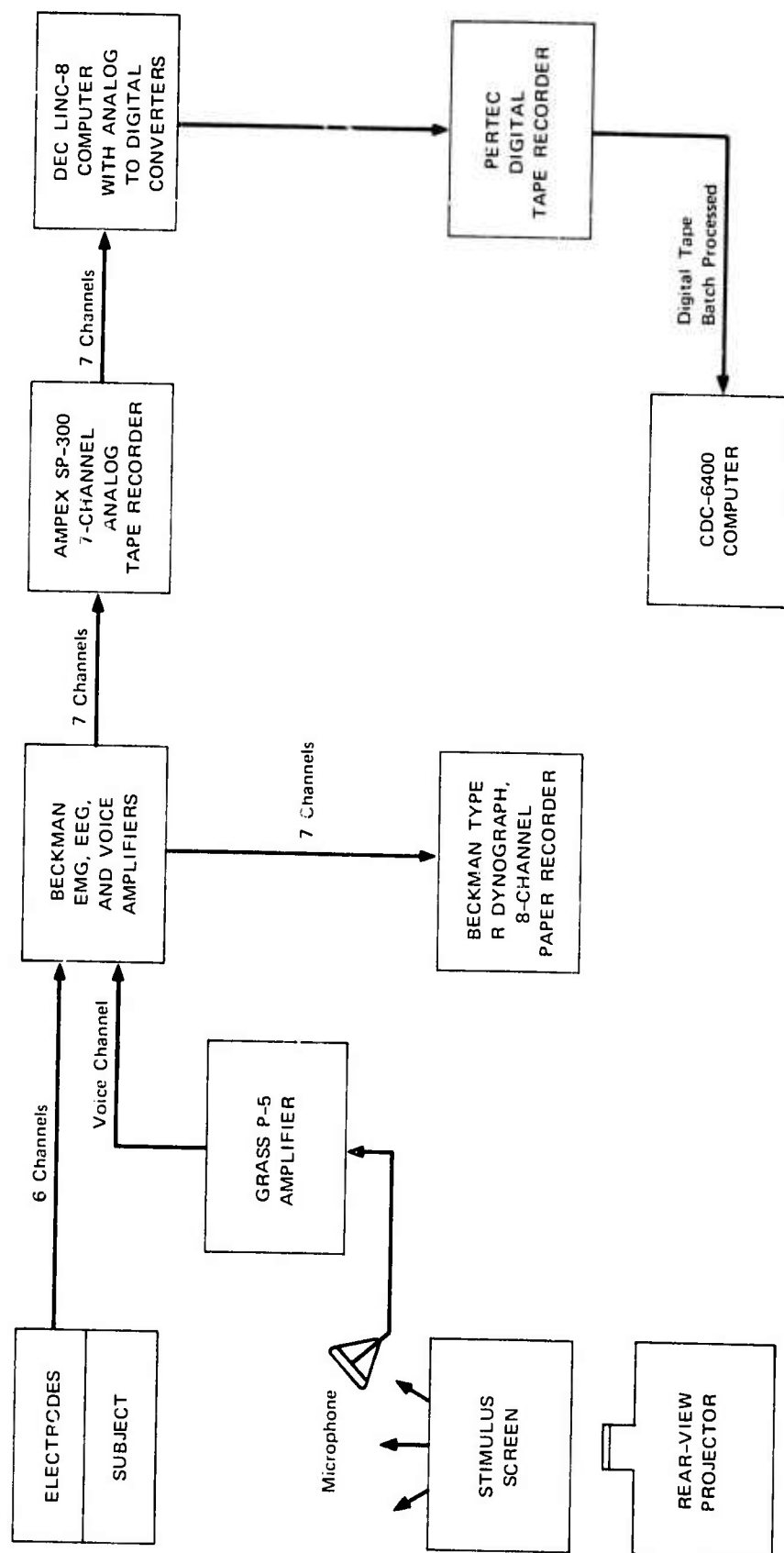


FIGURE 3 BLOCK DIAGRAM OF STIMULUS RECORDING AND DATA PROCESSING EQUIPMENT

Procedure

Language Task

On the basis of results from Group I data, 15 words were selected which had the greatest likelihood of reproducing reliable EMG patterns. The 15 words and a sentence containing all the words, which are shown in Table 1, consisted of five monosyllabic and five bisyllabic words. The latter are phonetically balanced words used in two groups; one group has the accent on the first syllable, and the other group has the accent on the second syllable. These 15 words were chosen to emphasize rounded lips, spreading lips, bilabials, and open lips in the case of the monosyllabic words, and to assess the effect of emphasis (pre- and post-) of one syllable on the other in the case of the bisyllabic words. No covert responses were obtained with Group II data.

Stimulus Presentation

Each of the individual words and the sentence in Table 1 was printed on a 35-mm slide (white on black to reduce glare) and presented to the S by projecting the word (or sentence) on a rear projection screen about 3 ft from the S's eyes. The subtended visual angle of the stimulus and its intensity in the semi-darkened room were chosen to avoid squinting, glare, or eye strain and to reduce eye movements.

After installation in the recording chamber, the S was instructed that she was to relax with eyes closed while the polygraph and tape recorder gains and filters were adjusted for proper EMG and EEG recordings. During that period, the S was to say her name when asked (to calibrate EMG gains and the voice channel) and to open or close her eyes when asked (to check for alpha in the closed-eyes EEG and alpha blocking, or desynchronization, with the eyes open and to check for eye movement artifact). Following these adjustments, the S was told that she would be presented with a list of 15 words, one at a time, for ten full presentations, plus one sentence at the end of each word list. The presentations would be visual. (The S was shown a test word on the screen as an example.) The S was to sit relaxed with her eyes closed. On hearing the statement "ready" from the experimenter, she was to open her eyes and look at the screen. In 2-3 sec. a stimulus word would be projected on the screen for about 3 sec, during which time she was to read the word aloud into the microphone. When the projected word was turned off, she was to close her eyes until the next word was presented, and wait until the next "ready" signal.

At the end of the 15 words (presented randomly to obviate any anticipatory effects in the EMG and EEG), the sentence was presented to the subject. On the signal "ready," the S was to open her eyes and look at the screen. When the sentence appeared, she was to read it aloud at her natural speed. The 15 words plus a sentence were then presented again; a total of ten such presentations were given each S per session.

Table 1

LANGUAGE TASK FOR GROUP II DATA

<u>Monosyllabic</u>	<u>Bisyllabic</u>	
	<u>Accent First Syllable</u>	<u>Accent Second Syllable</u>
TIP	<u>BLACK</u> BOARD	BLACK <u>BOARD</u>
HIT	<u>SCHOOL</u> BOY	SCHOOL <u>BOY</u>
HAD	<u>COUGH</u> DROP	COUGH <u>DROP</u>
PUT	<u>SHIP</u> WRECK	SHIP <u>WRECK</u>
COOL	<u>MOUSE</u> TRAP	MOUSE <u>TRAP</u>

Sentence:

THE SHIPWRECKED SCHOOLBOY HAD PUT A COOL COUGHDROP IN THE MOUSETRAP
AND AIMED IT TO HIT AND TIP OVER THE BLACKBOARD.

Each of the three Ss was run a second time not less than one week nor more than one month following the first session. This set of measurements was recorded exactly the same as the first, and was run to determine within S reliability. Thus Group II data are based on six electrodes per S, for three Ss, two sessions each, where each session consisted of ten repetitions of 15 words and one sentence. This resulted in a total of 5400 electrophysiological responses ($6 \times 3 \times 2 \times 10 \times 15$) of 6 sec each (this total does not reflect analysis of the sentences, which has not yet been completed and will be described in a later report).

Data Analysis

Editing and Digitizing

As noted in the First Semi-Annual Technical Progress Report, editing and digitizing of the Group II data for the CDC-6400 computer processing was delayed while waiting for installation of a Pertec digital recorder. When this was received in early December 1972, a Linc-8 program written for this purpose, was used to edit and digitize the analog data.

A synchronization signal on channel 7 (voice channel) of the Ampex analog recorder, which preceded each stimulus presentation, caused the Linc-8 to begin sampling the six channels of data and the voice channel through analog-to-digital converters. A total of 7 sec of data were sampled at 42 samples/sec for each of the seven channels. The 7th sec of data was collected for time justification of the electrophysiological response as described below. The data were stored in memory, and on command any two of the six data channels or the voice channel could be displayed on a two-channel, cathode-ray oscilloscope driven by the computer. The display itself consisted of 6 sec of data, or 256 data points. In addition, the scope displayed a vertical cursor that was exactly centered to represent a zero point for time justification of the electrophysiological response.

Figure 4 illustrates the seven-channel dynograph recording of the EMG and EEG for one presentation of the word "COOL." Note the cursor line at the onset of vocalization (channel 7) which was used to time-justify all electrode responses. Any two of these channels could be displayed on the Linc-scope, as shown in Figure 5. In Figure 5A, an EMG response is shown on the top channel; the voice voltage and the centered cursor are shown on the second channel. Note that the vocal onset is off-centered on the scope, indicating that this particular response was not time justified for vocalization to occur at exactly 3 sec from the onset of the display. By use of a second Linc-8 command, all six channels of data and the voice channel could be rotated simultaneously into and out of memory with the extra 7th sec to place the onset of vocalization at any desired point. This feature was used to shift the data and voice channels (to the left in this case) so that the onset of vocalization occurred at the centered, 3 sec cursor, as shown

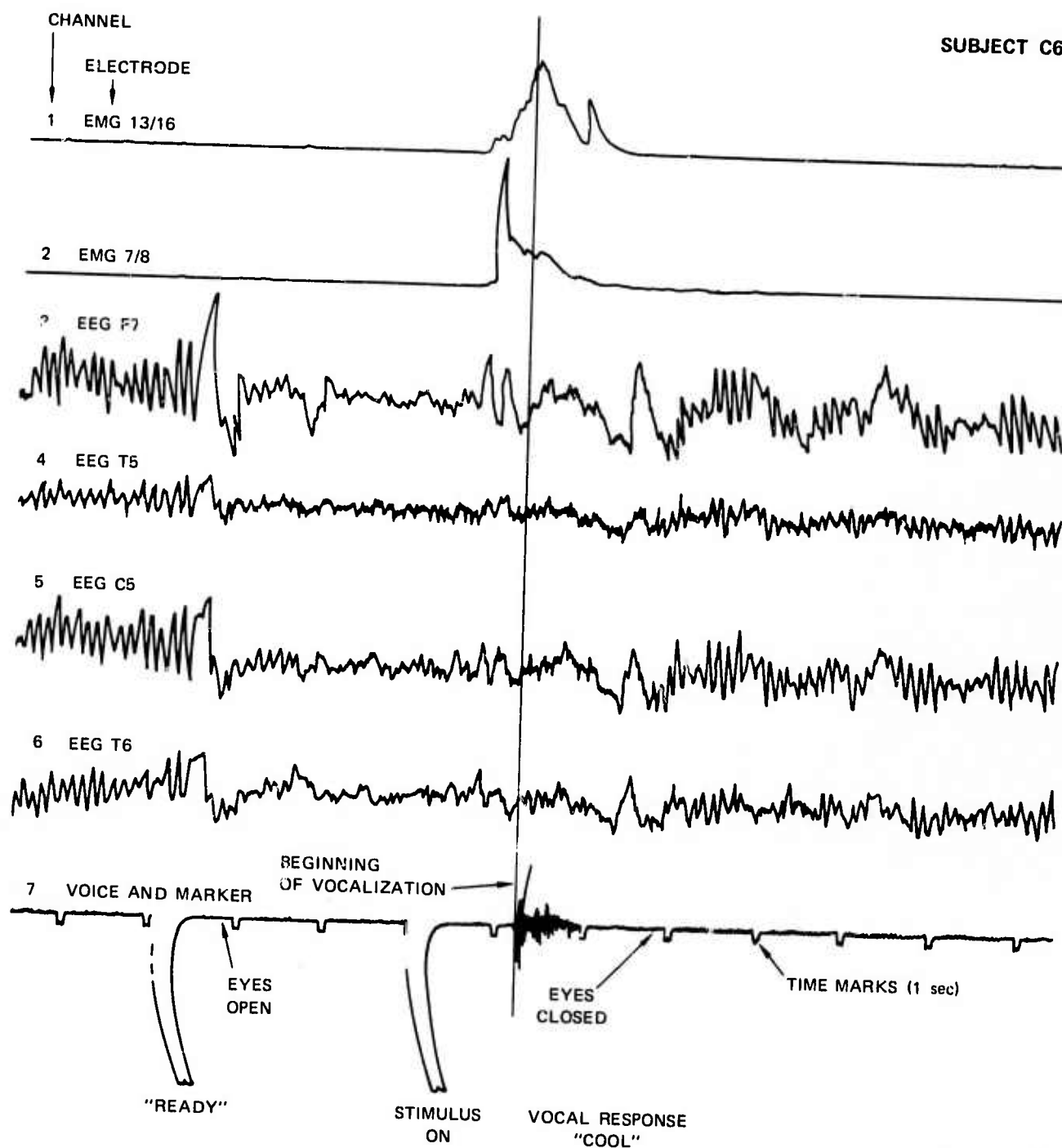


FIGURE 4 DYNOGRAPH RECORDING OF STIMULUS-RESPONSE OF EMG AND EEG FOR THE WORD "COOL"

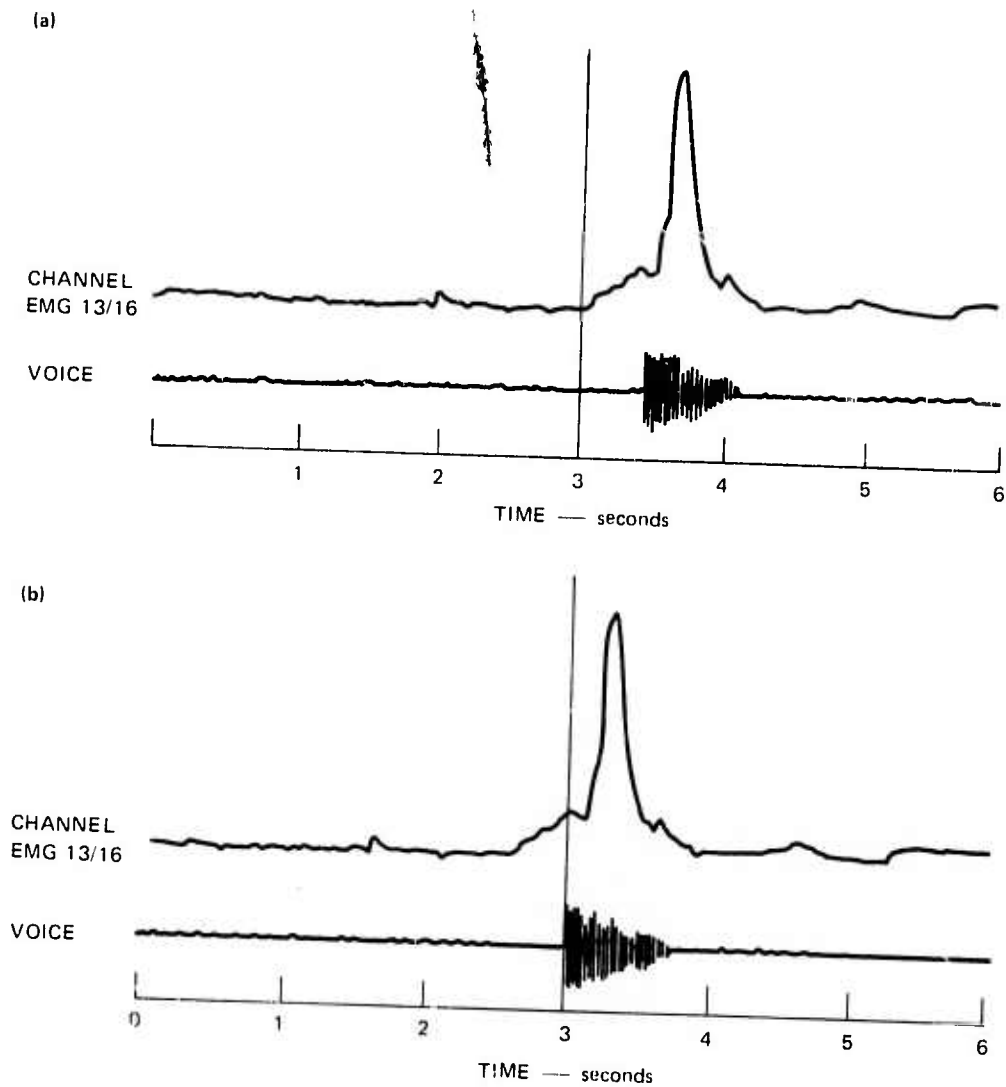


FIGURE 5 PLOTS OF LINC-8 CRT FOR TIME JUSTIFICATION OF ELECTROPHYSIOLOGICAL RESPONSE TO WORD TIP WITH ONSET OF VOCALIZATION AT $t = 3$ SECONDS

in Figure 5B. Thus, after time justification, 3 sec of data were displayed before the onset of vocalization and 3 sec after. On completion of time justification, the six channels of data were stored on Linc tape on the computer, one channel per block of tape. Then the next stimulus-word-response was sampled from the Ampex recorder, the responses were time justified, and the data stored.

When responses to all 150 word utterances and the 10 sentences for a given subject-session had been stored on Linc tape (six channels per word and sentence, for a total of 990 tape blocks), another Linc-8 program was used to transfer this data to the Pertec digital tape recorder in ten files of 101 records per file (255 samples per block were transferred rather than the 256 collected because of an error in the transfer program). The Pertec tape was then unpacked on the CDC-6400 computer, and the data words were reordered in sequence for data processing.

CDC-6400 Response Classification by Averaging

As a first approximation for machine pattern recognition of the six electrophysiological responses for each word utterance, it was decided to use a method of averages to construct templates for response-word classification. (The rationale and mathematical equations for this, and all other computations described below, are given in the Appendix.) The data unit of analysis for classification was the individual 6-sec electrode response corresponding to a word. To determine whether the CDC-6400 computer could correctly classify the word by analysis of the electrophysiological response alone, the response was compared with 15 templates (one for each of the 15 words).

As shown in Figure 6, a given template was the average electrophysiological, 6-sec response for the ten repetitions of the word for a given S on each session. Each sample point of the 255 samples in a 6-sec epoch was added to each corresponding point of the other nine responses, and the result divided by ten for the average response for that point. Since there were six electrodes and 15 words, there were 90 templates altogether for each S on each session, or a total of 540 templates for the three Ss, two sessions each.

To compare a single electrode response for a single word utterance with each of the 15 templates for that electrode, a root-mean-square (RMS) difference was calculated between the single response and the template, as shown in Figure 7. In the top of the figure the EMG 13/16 electrode response to TIP 2 (second utterance of TIP) is compared with the template for COOL. That is, each sample of the 255 samples in the response was subtracted from the corresponding sample in the template. The difference for each sample point (only a few fictitious values were used in Figure 7 for illustration) was squared, and the squared differences were summed over the 255 samples. Dividing by 255 and taking the square root provided the single RMS number for that comparison.

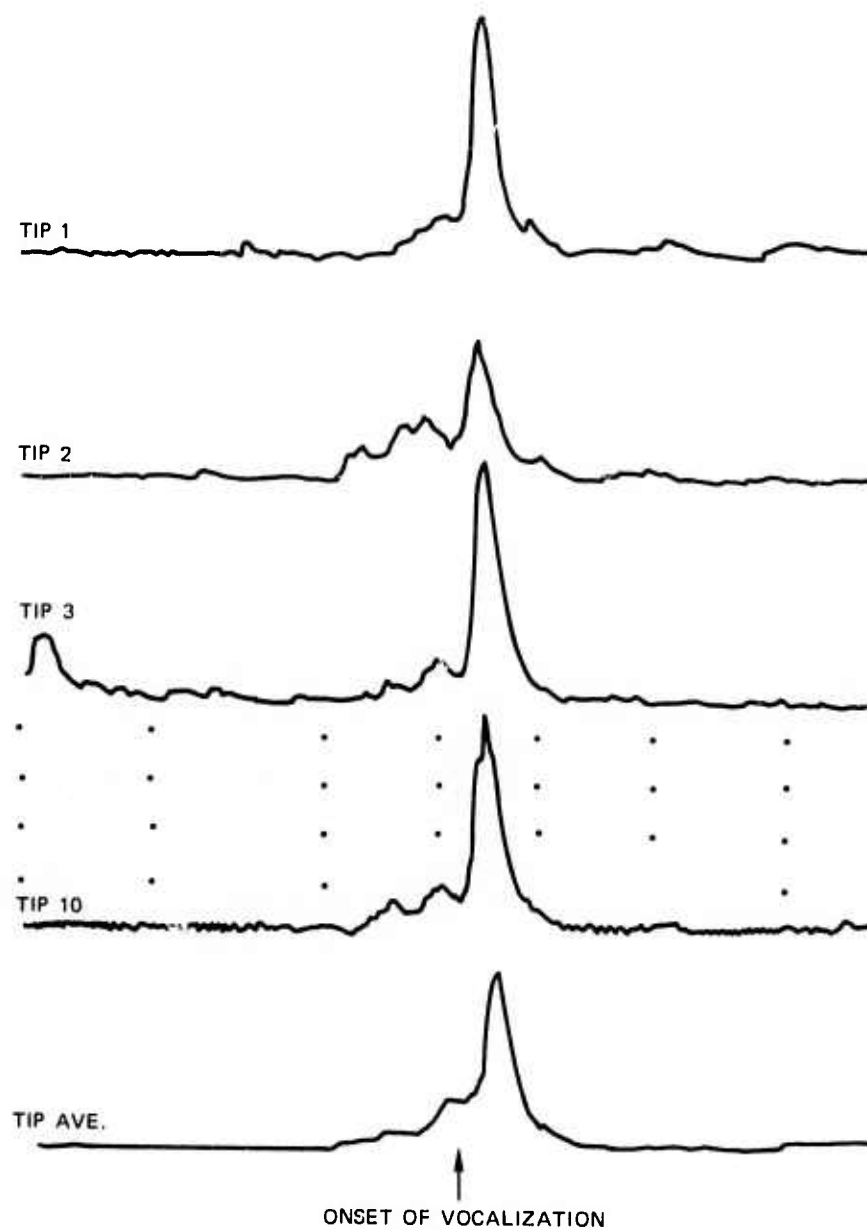
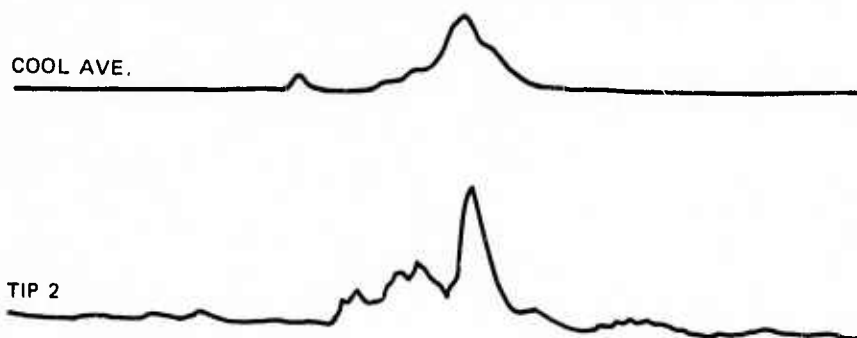


FIGURE 6 AVERAGING OF EMG RESPONSES (ELECTRODE 13/16) FOR WORD "TIP"

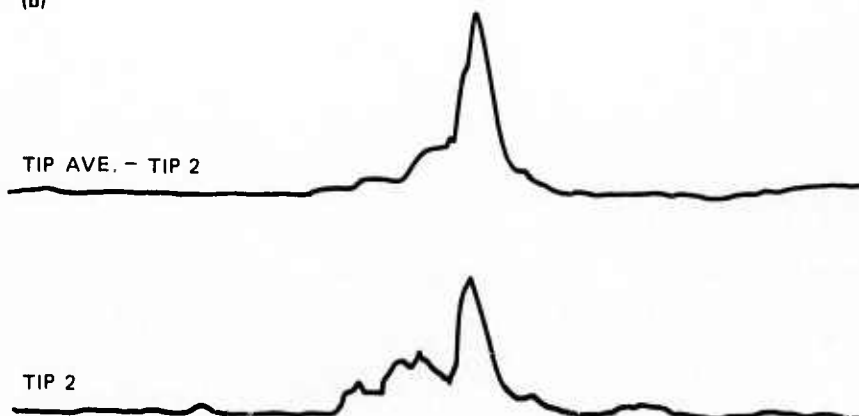
(a)



0	0	0	0	0	-3	-10	-15	-25	-6	-7	-2	0	0	0	DIFFERENCE
0	0	0	0	0	9	100	225	625	36	49	4	0	0	0	D ²

$$\text{RMS} = (\sum D^2 / 255)^{1/2} = 2.03$$

(b)



0	0	0	0	1	0	0	-1	5	2	3	4	-6	0	0	0	DIFFERENCE
0	0	0	0	1	0	0	1	25	4	9	16	36	0	0	0	D ²

$$\text{RMS} = (\sum D^2 / 255)^{1/2} = 0.60$$

FIGURE 7 CLASSIFICATION OF TIP 2 AS TIP WITH RESPECT TO ANOTHER TEMPLATE (COOL) USING RMS DIFFERENCE

In the bottom of Figure 7, the same electrode response to TIP 2 is compared with the template for the word TIP. Since TIP 2 was included in making the template for TIP (see Figure 6), this template was necessarily biased in favor of classifying TIP 2 response as TIP. Therefore, for this response and all other responses compared with their own templates, the individual response was first subtracted from the template. The RMS difference was then calculated for the individual response against the unbiased average response for the other nine utterances of the word.

After calculating the RMS difference for a given electrode response for a given word against all 15 templates, the computer then classified the response as the word having the smallest RMS value. For example, in Figure 7, TIP 2 is classified as "TIP" rather than "COOL," since the RMS difference with TIP AVERAGE minus TIP 2 is less than the RMS difference with COOL AVERAGE. If this RMS difference remained the smallest when TIP 2 was compared with all 15 templates, then ultimately the TIP 2 response was classified as TIP.

In this way, response classifications were made for each of the 150 words per S per session per electrode (Within Subjects, Within Sessions classification). Two additional classifications were also made: (1) Within Subjects and Between Sessions (to assess within S reliability); and (2) Between Subjects (to assess individual differences). In the first case, the six electrode responses for each 150 words of one session for a given S were compared to the 15 templates for the other session for that S (e.g., C5 responses with C6 templates, and C6 responses with C5 templates). In the second case, the six electrode responses for each of the 150 words of a given S on a given session were compared with the 15 templates for another S on a given session (e.g., C5 responses with B5 templates, or D4 responses with C6 templates).

Finally, in addition to obtaining classification of responses for each electrode, it was decided to pool both EMG electrodes, all four EEG electrodes, and all six electrodes (EMG plus EEG) to assess the relative contribution of types and number of electrode responses to the computer classification.

Determination of Critical Classification Period

The electrophysiological recordings shown earlier in Figure 4 to the word COOL illustrate that only about 1 sec of the 6-sec epoch is actually involved in making the response. Since it is possible that computer classification of an electrophysiological response might be based on that portion of the response following stimulus onset, but before the onset of vocalization, it was decided to determine which parts of the 6-sec epoch contributed to the classification and to what extent. To do this, an F-ratio was calculated for each electrode for the Within Words variance and Between Words variance for each of the 255 data samples in the 6-sec epoch (see Appendix for details of computation). If a given sample point was not contributing to the computer

classification of the word, then the ratio of the two variances (i.e., the F-statistic) should be small. On the other hand, if the Between Word variance was significantly higher than the Within Word variance for a given sample point, then it may be assumed with some confidence (given by statistical tables for the F-ratio) that the particular data point was contributing to the classification.

Examples of the F-ratio for the 255 samples in the 6-sec epoch for an EMG and an EEG electrode are shown in Figures 8 and 9, respectively, for Subject C, Session 5. Note that in both cases the F-ratio remains small and statistically insignificant for about the first 100 samples, but becomes and remains significantly larger from about sample 101 to about sample 200. For the EEG (Figure 9), another portion between about sample 205 through 230 barely reaches significance. This means that for both EMG and EEG responses taken separately, only that portion of the 6-sec epoch between samples 101 and 200 probably contributes significantly to classification of the response (that portion of the EEG from 205 to 230 may also contribute, although less significantly). F-ratios were calculated for all Ss, sessions, and electrodes, with essentially the same results.

The finding that the samples from 101 to 200 of a response are the only portion of the response contributing to the classification suggested that calculating sums of squared differences for RMS values across all 255 samples may produce undesirable errors. Accordingly, each electrode response was further divided into three subgroups, and RMS values were calculated and responses classified for each subgroup, as well as for the entire 255 samples. These subgroups were samples 1-100, 101-200, and 201-255. Thus, for each of the six electrodes taken separately, the two EMG electrodes taken together, the four EEG electrodes taken together, and all six electrodes taken together, there were four classification epochs for a total of 36 classifications per word per S per session.

CDC-6400 Response Classification by Other Statistics

As pointed out earlier, there is no a priori reason for believing that a particular statistic of the EEG and EMG will ultimately be a better classifier of the verbal response than any other. Consequently, several other statistics were computed, RMS differences were obtained in the same manner as with the averaged responses, and individual electrode responses were classified. These statistics were auto- and cross-spectra, linear coherence, and weighted-average coherence (see the Appendix for the meaning of these statistics and details of their computations). These statistics are presumed to be useful, since they involve frequency analysis of the EEG and may be used to determine the degree of interaction between two or more different regions of the brain. Such an analysis should provide information about cortical organization, and therefore may show patterns of organization that are specific for particular responses to the 15 stimulus words. Except for the actual calculation of the statistic itself, all other computations for response classification were the same as for the averaged responses described above.

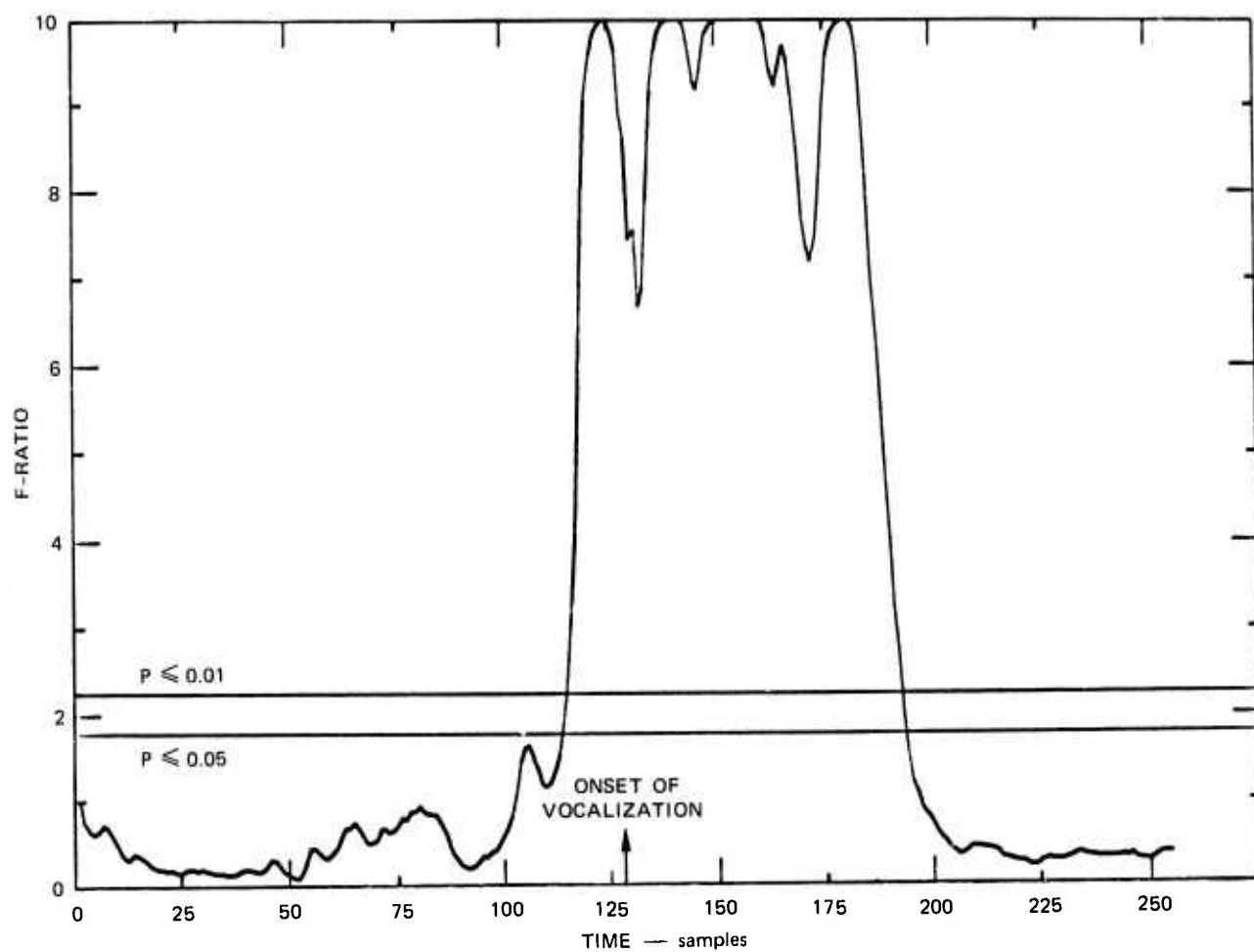


FIGURE 8 F-RATIOS FOR EMG ELECTRODE 13/16, SUBJECT C5, ALL WORDS

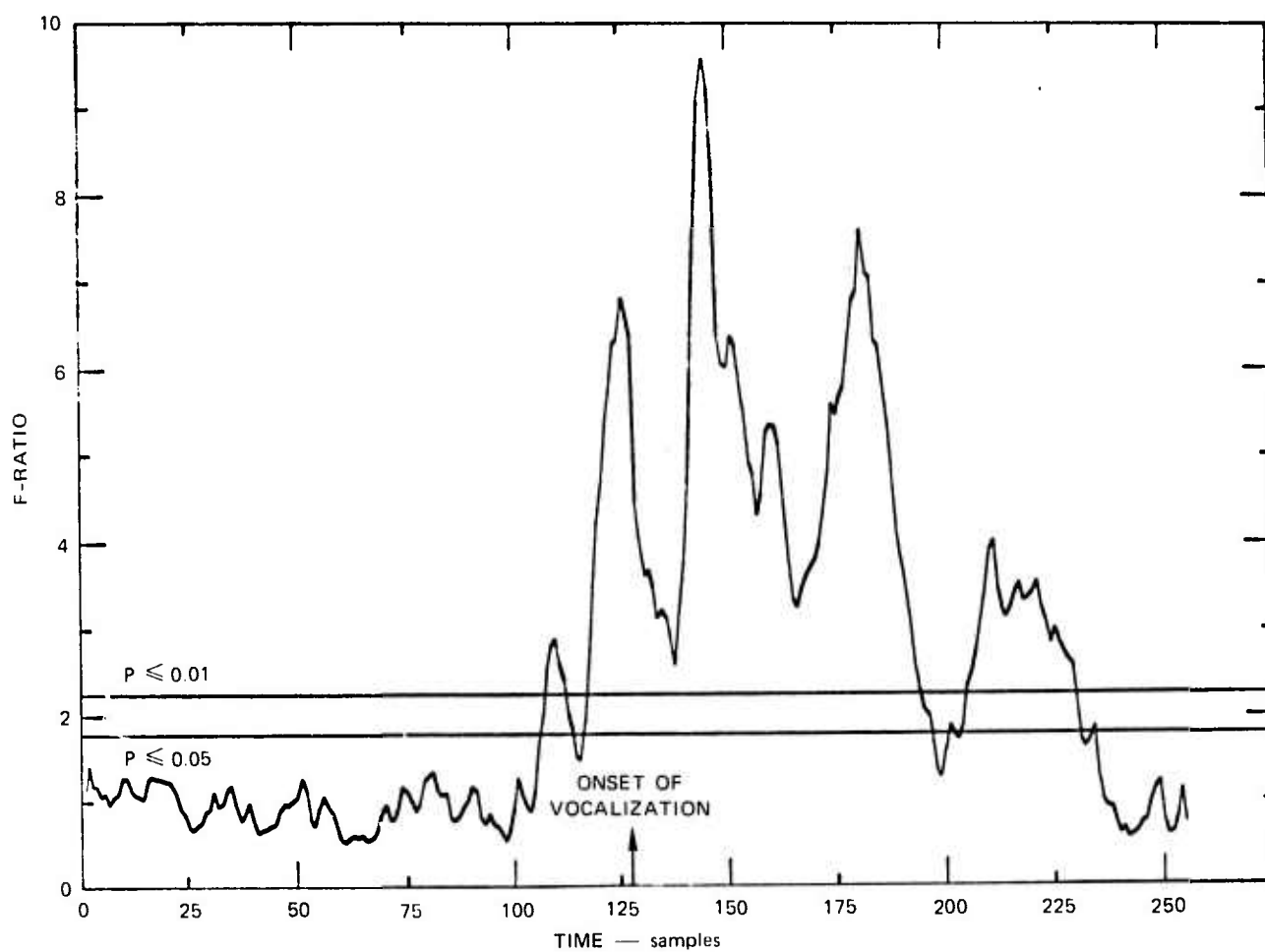


FIGURE 9 F-RATIOS FOR SUBJECT C5, EEG ELECTRODE F7, ALL WORDS

Tests for Statistical Significance

To show that correct classification of single electrode responses by the computer did not occur by chance, a chi square was calculated for each electrode subclassification for each S and each session, between sessions and between subjects. The "expected" frequencies for evaluating the chi square were based on classifications being randomly distributed across words (see the Appendix for details of computation).

Control of Artifact

In a working biocybernetic communication system, constraints on the user against eye or muscle movement may not be effective. Since such movements often produce artifacts in electrophysiological responses (especially in the EEG), it is imperative that a system be designed that is not unduly affected by such artifacts. That is, pattern recognition and classification should be carried out successfully whether artifacts are present or not. For this reason, it was decided to analyze Group II data without removing those responses with known artifacts present; that is, this was a "worst case" analysis.

Nevertheless, some effort was devoted to controlling and identifying artifacts, and to assessing their contribution to response classification. This was accomplished by obtaining responses in the four EEG electrodes to five words under conditions of both visual and auditory stimuli and with and without known eye movements and movement artifacts. The results of these controlled studies are described below under "Results, Group II Data, Sources of Error." Finally, during data collection proper, Ss were instructed to remain as relaxed as possible during the response period, with no more eye or body movement than necessary.

RESULTS OF GROUP II DATA

Classification by Averages

Individual Responses

Figure 10 illustrates the six electrode templates for Subject C, Session 5, for the word COUGHDROP, with the accent on the first syllable. Note that for both EMG and EEG records, significant changes occur primarily over computer samples 101 to 200, thus beginning about 0.5 sec before onset of vocalization (arrow at 3.0 sec).

Figure 11 shows the variability around the averages of Figure 10, the upper trace of each pair being the average plus one standard deviation, the lower trace the average minus one standard deviation. Note that the variability of each electrode signal is relatively small. Similar plots were made for all three Ss for the two sessions, each with essentially similar results, indicating that it should be feasible to identify a given spoken word by comparing the electrophysiological response to the templates.

As described in the previous section, for each S on each session, the individual electrode response for each of the 150 word utterances was compared with the 15 templates. These comparisons resulted in 15 RMS values, from which the CDC-6400 computer classified the response with the word for which the RMS value was a minimum. Tables of correct responses were then constructed for each S and each session, showing the number of correct classifications for the 150 words for each electrode and each subclassification.

Table 2 shows these results for Subject C, Session 5, and illustrates the method. Along the top row are the 15 words. The leftmost column gives the channel number (corresponding to Figure 4) for the six electrodes, the combination of both EMG electrodes, the combination of the four EEG electrodes, and the combination of all six electrodes. The second column on the left gives the four subclassifications for each electrode and combination--that is, the sample points of the 6-sec response over which classifications were made according to the findings of the F-ratios (see previous section). The table proper then gives the number of responses correctly classified for each electrode and each subgroup. For example, in Channel 1 (EMG electrode 13/16), in the portion of the response from sample 1-100, none of the utterances of TIP was correctly classified, while six out of ten were correctly classified for samples 101-200, none for samples 201-255, and five for the entire response (samples 1-255). The same interpretation can be made for all other words, electrodes, and combinations.

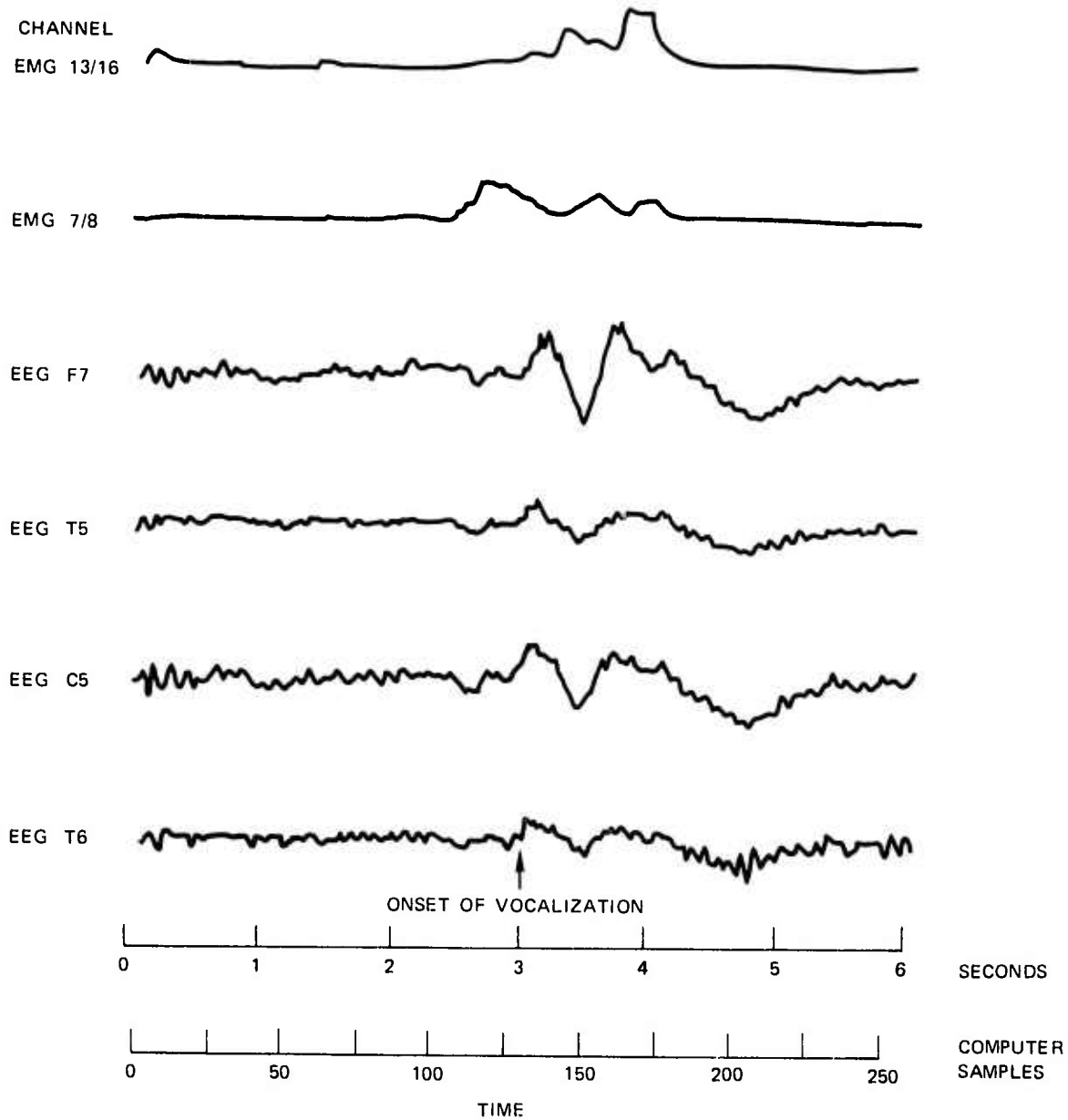


FIGURE 10 TEMPLATES (AVERAGES OF 10 RESPONSES EACH) FOR THE SIX ELECTRODES, SUBJECT C5, FOR THE WORD COUGHDROP

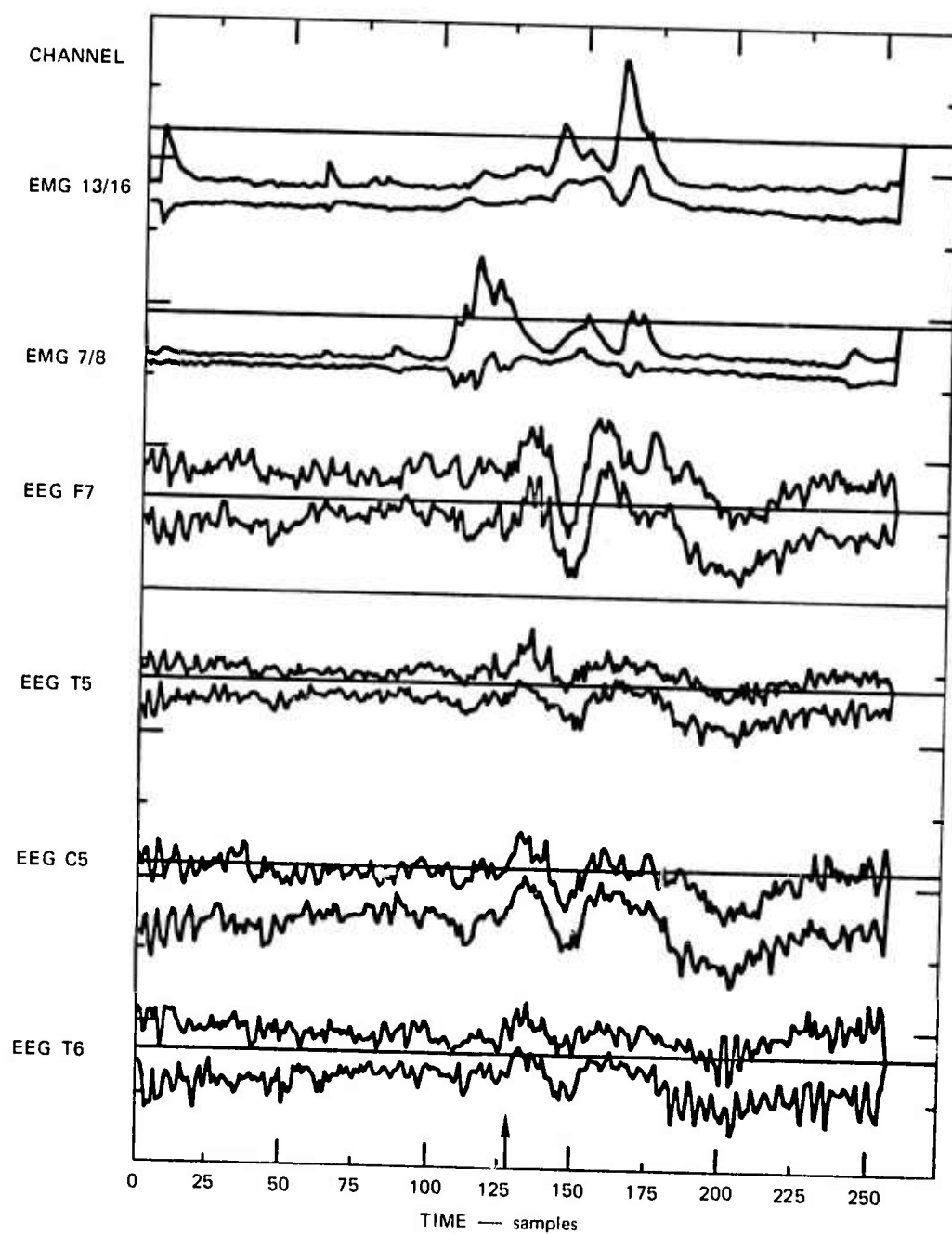


FIGURE 11 VARIABILITY OF AVERAGE RESPONSES OF THE SIX ELECTRODES, SUBJECT C5, FOR THE WORD COUGHDROP

Table 2

FREQUENCY OF CORRECT RESPONSE CLASSIFICATION, SUBJECT C5

SUMMARY TABLE, MARCH 7, 1973														
WITHIN SESSION SUMMARY OF COMPARISON DATA														
S1=SCHOOLBOY 1 S1=5HIPWRECK 1 C01=COUG+DROP 1 MT1=MOUSETRAP 1														
S2=SCHOOLBOY 2 S2=5HIPWRECK 2 C02=COUG+DROP 2 MT2=MOUSETRAP 2														
SUMMED OVER THE FOLLOWING DATA SETS														
C5 DATA WITH C5 TEMPLATES 1-100+101-200+201-255														
NUMBER OF RESPONSES CORRECTLY CLASSIFIED														
REPETITIONS	TIP	MAD	PUT	COOL	MIT	S01	S01	S01	S01	S01	S01	S01	S01	S01
CHAN POINTS	10	10	10	10	10	10	10	10	10	10	10	10	10	10
1 1-100 1	0	0	1	0	0	0	0	0	0	0	0	0	0	0
101-200 2	6	5	8	8	6	5	6	5	6	5	6	5	6	5
201-255 3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1-255 4	5	5	8	8	5	5	5	5	5	5	5	5	5	5
2 1-100 5	0	2	0	1	1	1	0	0	0	0	0	0	0	0
101-200 6	5	1	2	5	6	4	5	4	5	4	5	4	5	4
201-255 7	0	0	0	1	1	0	0	0	0	0	0	0	0	0
1-255 8	5	1	2	4	6	3	5	4	5	4	5	4	5	4
3 1-100 9	0	0	1	1	2	0	0	0	0	0	0	0	0	0
101-200 10	6	5	6	4	1	4	5	3	5	5	5	4	5	4
201-255 11	2	2	3	1	1	0	0	2	1	0	0	1	0	0
1-255 12	6	4	5	2	3	1	3	2	3	5	1	3	4	4
4 1-100 13	0	1	0	0	0	0	0	1	0	0	0	0	0	0
101-200 14	6	3	4	9	5	4	3	3	4	3	4	7	8	4
201-255 15	1	0	2	0	4	0	1	1	0	0	0	0	1	1
1-255 16	5	2	3	7	3	4	3	2	2	2	3	4	4	1
5 1-100 17	0	0	1	1	0	0	0	1	0	0	0	0	0	0
101-200 18	7	5	5	6	2	3	3	3	3	1	3	5	3	4
201-255 19	2	1	1	1	0	0	1	2	0	1	0	1	0	0
1-255 20	4	2	4	6	2	2	5	2	2	5	2	3	4	3
6 1-100 21	1	0	0	0	1	2	1	0	0	1	1	1	1	4
101-200 22	4	1	2	3	2	3	3	1	4	2	2	4	3	2
201-255 23	0	1	1	0	0	1	4	0	0	1	0	0	0	0
1-255 24	5	1	1	0	1	3	3	0	0	2	1	3	2	2
EMG 1-100 25	0	2	0	0	2	0	0	0	1	0	2	0	0	0
1-201-200 26	5	5	8	9	6	8	7	3	6	7	2	9	4	7
201-255 27	0	1	0	0	3	0	0	2	0	0	1	0	0	0
1-255 28	5	4	8	9	6	7	7	4	6	7	3	9	3	7
EEG 1-100 29	0	0	0	0	0	0	0	1	0	0	0	1	0	0
3-0101-200 30	6	5	6	7	2	4	4	3	3	4	6	5	5	3
201-255 31	2	1	1	0	0	0	1	0	0	1	0	1	2	0
1-255 32	6	3	4	3	1	1	4	1	3	3	3	3	5	4
ALL 1-100 33	0	0	0	0	1	0	0	1	0	0	0	1	0	3
1-0101-200 34	8	5	8	9	7	8	8	5	8	7	4	9	5	5
201-255 35	1	0	1	0	0	0	1	1	0	1	0	1	2	0
1-255 36	7	4	8	9	6	5	8	4	6	7	4	9	4	7

On the far right, under the column labeled "Correct," the total number of responses across the 15 words that were correctly classified is listed for each electrode and combination for each subgroup. Thus, for Channel 1, 4 out of 150 individual responses were classified correctly for subgroup 1-100, 86 out of 150 for subgroup 101-200, 7 out of 150 for subgroup 201-255, and 83 out of 150 for the total response (1-255). Note that for all electrodes and combinations, the middle subgroup (101-200) is a better classifier than any other subgroup including the total response (1-255), as predicted by the F-ratio test. The latter result means that variation in the responses outside of the 101-200 sample period serves to decrease the accuracy of classification. Furthermore, all electrodes taken together (see "All" data at the bottom of Table 2), especially in the 101-200 subgroup, serve as a better classifier than any single electrode or combination. Thus, for the 101-200 sample subgroup, 105 out of 150 (or 70%) of responses were correctly classified. Table 2 also shows that for this S and session, the EMG responses (individually or taken together) were better classifiers than any (or all) of the EEG responses, and that the EEG of the nondominant hemisphere (T6, Channel 6) was the poorest classifier of all.

The two columns on the right of Table 2 give the chi square values for Within Words (CHI 1=1 degree of freedom) and Between Words (CHI 15=15 degrees of freedom). These indicate how likely the total number of correct classifications was obtained by chance. The chi square for significance at the $p < .01$ level is 30 for this distribution and 15 degrees of freedom. Thus, all correct classifications in the "Total Correct" column having a chi square greater than 30 occurred by chance with a probability of less than 1 out of 100. Examination of this column shows that only the 101-200 and 1-255 sample subgroups were at high levels of significance for all electrodes and combinations.

Finally, the third row from the bottom of Table 2 ("All electrodes," subgroup 101-200, the best classifier of all) shows the frequency of the words that were correctly classified for Subject C, Session 5. Thus, three words (COOL, BLACKBOARD, and MOUSETRAP) were correctly classified nine times out of ten, while five words were correctly classified 80% of the time, two 70%, four 50%, and one 40%.

Within Subjects

To test the reliability of measurements and response classification, all three Ss were run on two sessions each. The sessions were no less than one week and no longer than one month apart. Tables of correct classifications were constructed for each S and each session (as in Table 2), and comparisons were made for both Within Subjects/Within Sessions, and Within Subjects/Between Sessions.

Table 3 summarizes the Within and Between Sessions comparisons for Subject C, for the best classifier subgroup (101-200) for all electrode combinations (Tables 4 and 5 give the results for Subjects B and D, respectively). The nearest percentage correct responses and the rank

Table 3

NEAREST PERCENTAGE CORRECT RESPONSES AND RANK ORDER OF ELECTRODES
AS CLASSIFIERS, SAMPLE POINTS 101-200, SUBJECT C, WITHIN AND BETWEEN SESSIONS

Channel	Within Sessions				Between Sessions			
	C5 with C5*		C6 with C6		C5 with C6**		C6 with C5	
	% Correct	Rank	% Correct	Rank	% Correct	Rank	% Correct	Rank
1	57	3	76	2	39	3	53	3
2	43	7	56	4	33	4	40	4
3	45	6	48	5	22	7	15	9
4	47	5	46	7	31	6	29	6
5	39	8	36	9	14	9	28	7
6	26	9	37	8	21	8	25	8
EMG	63	2	79	1	42	2	64	2
EEG	49	4	47	6	31	5	31	5
All	70	1	75	3	50	1	65	1

* C5 data compared with C5 templates.

** C5 data compared with C6 templates.

Table 4

NEAREST PERCENTAGE CORRECT RESPONSES AND RANK ORDER OF ELECTRODES
AS CLASSIFIERS, SAMPLE POINTS 101-200, SUBJECT B, WITHIN AND BETWEEN SESSIONS

Channel	Within Sessions				Between Sessions			
	B5 with B5*		B6 with B6		B5 with B6**		B6 with B5	
	% Correct	Rank	% Correct	Rank	% Correct	Rank	% Correct	Rank
1	49	3	57	4	32	4	52	3
2	59	2	59	3	56	3	51	4
3	9	9	22	8	19	9	23	9
4	29	7	14	9	23	8	24	8
5	31	6	27	7	25	6	37	5
6	38	5	29	5	29	5	30	6
EMG	67	1	74	1	61	2	67	1
EEG	12	8	29	6	24	7	28	7
All	47	4	67	2	63	1	65	2

* B5 data compared with B5 templates.

** B5 data compared with B6 templates.

Table 5

NEAREST PERCENTAGE CORRECT RESPONSES AND RANK ORDER OF ELECTRODES
AS CLASSIFIERS, SAMPLE POINTS 101-200, SUBJECT D, WITHIN AND BETWEEN SESSIONS

Channel	Within Sessions				Between Sessions			
	D3 with D3*		D4 with D4		D3 with D4**		D4 with D3	
	% Correct	Rank	% Correct	Rank	% Correct	Rank	% Correct	Rank
1	66	3	72	2	56	3	56	4
2	67	2	71	3	59	2	65	2
3	19	7.5	27	8	11	8.5	11	8.5
4	27	5	30	7	12	7	11	8.5
5	16	9	33	6	15	6	16	7
6	19	7.5	19	9	24	5	17	5.5
EMG	74	1	84	1	67	1	71	1
EEG	25	6	37	5	11	8.5	17	5.5
All	65	4	70	4	50	4	57	3

* D3 data compared with D3 templates.

** D3 data compared with D4 templates.

order of electrodes as classifiers are given by classifying each response first with the templates of its own session, and then with the templates from the other session. The following may be concluded from inspection of Tables 3, 4, and 5:

- (1) In all three Ss, a greater number of responses were correctly classified on the second session (Within Sessions comparison) than on the first (by rank order and not necessarily for a particular electrode or combination). Thus, an habituation or learning effect is present that, presumably, reduces the variability from one session to the next.
- (2) Again in all three Ss, when the second session responses are compared with the first session templates (Between Sessions comparisons), a greater number of responses were classified correctly than when the first session responses are compared with the second session templates. This is also probably due to a decreased variability in the individual responses of the second session, further strengthening the conclusion that habituation or learning operates to improve performance in response classification.
- (3) In all three Ss, the EMG responses, taken separately or together, are better classifiers than any EEG response or the EEG responses taken together. However, there appears to be no consistency, either within a S or across Ss, for any particular EEG response being a better classifier than any other.
- (4) The range of percentages of correct classifications across Ss is from 9% to 84%, with all EMG and all electrodes generally in the higher ranges, EMGs separately and all EEGs in the middle range, and EEGs separately in the lower ranges.
- (5) Comparisons among percentages of correct responses among the three Ss indicate that responses from Subject C are better classifiers, in general, than either B's or D's, with B slightly better than D. Examination of either raw data or templates shows that this result is probably due to variability (larger in D, less in B, still less in C).

Tables 6 and 7 give summaries for all Ss and sessions together for Within Subjects/Within Sessions comparisons, and Within Subjects/Between Sessions comparisons, respectively. These tables are to be interpreted as is Table 2. They show that for all Ss and sessions, the results are essentially the same as for Subject C, Session 5. That is, the number of correctly classified responses (out of a possible 900) is 74% for EMGs, 63% for all electrodes, and about 34% for EEGs. Again, this is true only for subgroups 101-200 and 1-255, the former being the better classifier of the two. All chi squares for these two subgroups (last two columns on the right for 1 and 15 degrees of freedom, respectively) were significant at p well below .001.

Table 7

SUMMARY OF CORRECT RESPONSE CLASSIFICATIONS FOR ALL SUBJECTS AND SESSIONS, WITHIN SUBJECTS AND BETWEEN SESSIONS

SUMMARY TABLES, MARCH 7, 1973									
COMPARISON BETWEEN SESSIONS FOR THE SAME SUBJECT									
SUBJECT		SESSION		CORRECT		WRONG		TOTAL	
1	2	1	2	1	2	1	2	1	2
SH2SCHOLMOY	SH2SCHOLMOY	SH2SCHOLMOY	SH2SCHOLMOY	SH2SCHOLMOY	SH2SCHOLMOY	SH2SCHOLMOY	SH2SCHOLMOY	SH2SCHOLMOY	SH2SCHOLMOY
SUMMARY OVER THE FOLLOWING DATA SETS									
DATA WITH H6 TEMPLATES									
DATA WITH H6 TEMPLATES									
DATA WITH C4 TEMPLATES									
DATA WITH C4 TEMPLATES									
DATA WITH D3 TEMPLATES									
DATA WITH D3 TEMPLATES									
NUMBER OF RESPONSES CORRECTLY CLASSIFIED									
REPEATITIONS	TIP	HAD	PUT	COOL	HIT	MISS	NO	YES	NO
CHANGES	6	6	6	6	6	6	6	6	6
1	1-100	1	2	3	9	3	2	5	4
101-200	2	27	31	26	27	24	35	31	2
201-255	3	5	1	6	5	7	2	9	4
1-255	4	26	24	24	24	24	37	32	31
2	1-100	5	3	5	3	9	6	2	1
101-200	5	24	33	35	29	25	35	28	2
201-255	7	6	2	4	4	7	3	4	2
1-255	4	26	23	32	35	23	34	27	26
3	1-100	9	1	0	2	0	11	1	4
101-200	10	21	9	11	11	3	5	15	7
201-255	11	12	3	0	0	3	1	15	8
1-255	12	17	8	10	11	7	12	20	14
4	1-100	13	5	4	1	4	2	9	0
101-200	14	13	11	15	16	15	6	15	9
201-255	15	1	4	11	4	9	2	2	0
1-255	16	7	13	19	20	16	5	16	4
5	1-100	17	5	4	1	1	1	3	2
101-200	18	20	18	6	16	14	13	21	12
201-255	19	4	0	8	9	8	5	1	7
1-255	20	16	12	9	27	9	5	17	7
6	1-100	21	2	4	0	3	1	4	2
101-200	22	13	17	15	18	22	12	21	9
201-255	23	4	7	8	7	9	3	1	3
1-255	24	10	17	11	15	14	6	11	7
EMG	1-100	25	2	4	4	3	9	3	6
1-2101-200	26	39	26	40	40	33	35	41	39
201-255	27	3	3	6	5	12	2	7	4
1-255	28	40	28	39	40	32	33	41	17
EEG	1-100	29	6	1	0	2	3	8	1
3-6101-200	30	22	11	20	20	6	8	24	8
201-255	31	11	8	7	4	5	3	2	6
1-255	32	22	12	12	21	8	7	25	12
ALL	1-100	33	9	1	0	2	2	6	2
1-6101-200	34	48	40	37	47	31	22	43	29
201-255	35	13	10	8	4	5	3	1	6
1-255	36	47	30	27	43	30	16	43	21

The comparison of Between Session (Table 7) with Within Sessions (Table 6) for all Ss and sessions repeats the findings shown in Tables 3, 4, and 5--namely, that Within Sessions responses are correctly classified with a higher frequency than the Between Sessions responses. The results of these five tables also show that intrasubject reliability is good.

Between Subjects

The results of the EMG analysis from Group I data (see Introduction) showed that an individual's electrophysiological responses accompanying speech are unique to that individual. Therefore, a comparison was made Between Subjects for one session for all combinations. The results of this comparison are shown in Tables 8 and 9. Table 8 gives the number of correct classifications for all subgroups, and their associated chi squares, while Table 9 compares percentage correct responses and electrode rank order for all Ss over all sessions. Table 8 shows that a significant number of EMG responses were correctly classified above chance level.

Table 9 shows that even though the EMG responses are significant at $p < .01$, the highest frequency (both EMG) is only 39%, compared with 74% Within Subjects/Within Sessions, and 62% Within Subjects/ Between Sessions. These results suggest that homologous muscles act more like each other between Ss than homologous brain sites. Table 9 also shows that, although EMGs taken separately or together are better classifiers than the EEGs taken separately or together, no EEG electrode is preferred for classification purposes.

Sources of Error

As indicated in Data Analysis section of Methods, no special attempts were made to remove artifacts or other known sources of error, because we wanted to see how well the computer would perform in classifying responses under the "worst case" condition. Several known sources of error existed, including time and amplitude variations and muscle and eye movement artifacts. Each of these is demonstrated below, and an evaluation made as to their relative contribution.

Confusion Matrices (Bisyllabic Confusion)

To determine why those responses not correctly classified were confused with other templates, a set of confusion matrices was constructed for each electrode, for each S, and for each session. Table 10 shows such a confusion matrix for Subject C, Session 5, for the "All Channels" category, for each of the four sample subgroups. The confusion matrix shows how each electrode response was classified. Note that for subgroups 1-100 and 201-255 (left side of table), the rates of correct classifications are quite low and appear to be randomly distributed. This is in contrast with subgroups 101-200 and 1-255 (right side of table),

Table 9

NEAREST PERCENTAGE CORRECT RESPONSES AND RANK ORDER OF ELECTRODES
AS CLASSIFIERS, SAMPLE POINTS 101-200, ALL SUBJECTS, ALL SESSIONS

<u>Channel</u>	<u>Within Sessions/ Within Subjects</u>		<u>Between Sessions/ Within Subjects</u>		<u>Between Subjects</u>	
	<u>% Correct</u>	<u>Rank</u>	<u>% Correct</u>	<u>Rank</u>	<u>% Correct</u>	<u>Rank</u>
1	63	3	48	4	27	2
2	59	4	51	3	24	3
3	28	8	17	9	8	6.5
4	35	5	22	7.5	7	8.5
5	30	7	22	7.5	7	8.5
6	28	9	24	5	8	6.5
EMG	74	1	62	1	39	1
EEG	33	6	24	6	9	5
All	65	2	58	2	22	4

Table 10

CONFUSION MATRIX, SUBJECT C, ALL CHANNELS

SUMMARY TABLE, MARCH 7, 1973

WITHIN SESSION SUMMARY OF COMPARISON DATA

SUMMED OVER THE FOLLOWING DATA SETS

CS DATA WITH CS TEMPLATES 1-100, 101-200, 201-255

NUMBER OF REPETITIONS PER WORD

TIP	HAD	PUT	COOL	MIT	SBI	BB1	SW1	CD1	MT1	SB2	BB2	SW2	CU2	MT2
10	10	10	10	10	10	10	10	10	10	10	10	10	10	10

CONFUSION MATRIX

ALL CHANS DATA, (CATEGORIES 33-36)

SAMPLES 1-100

SAMPLES 101-200

WORD	GETS	CLASSIFIED	AS	IF	IT	WERE	---	WORD	GETS	CLASSIFIED	AS	IF	IT	WERE	---
TIP	TIP	HAD	PUT	COOL	MIT	SBI	BB1	SW1	CD1	MT1	SB2	BB2	SW2	CU2	MT2
TIP	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
HAD	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PUT	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
COOL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MIT	2	1	1	0	0	0	0	0	0	0	0	0	0	0	0
SBI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BB1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SW1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CD1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MT1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
SB2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
BB2	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
SW2	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0
CU2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MT2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

SAMPLES 201-255

WORD	GETS	CLASSIFIED	AS	IF	IT	WERE	---	WORD	GETS	CLASSIFIED	AS	IF	IT	WERE	---
TIP	TIP	HAD	PUT	COOL	MIT	SBI	BB1	SW1	CD1	MT1	SB2	BB2	SW2	CU2	MT2
TIP	1	2	1	1	0	0	0	0	0	0	0	0	0	0	0
HAD	1	0	3	1	1	0	0	0	0	0	0	0	0	0	0
PUT	0	5	1	1	2	0	0	0	0	0	0	0	0	0	0
COOL	1	1	4	0	0	0	0	0	0	0	0	0	0	0	0
MIT	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
SBI	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0
BB1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
SW1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
CD1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
MT1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SB2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BB2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SW2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CU2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MT2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

where a strong diagonal begins at the upper left, each cell of the diagonal representing the number of correct responses.

The diagonal is seen even more clearly in Tables 11 and 12, which present the confusion matrices for all Ss Within sessions and Between Sessions, respectively. There are also two strong subdiagonals in subgroups 101-200 and 1-255. The first begins at the junction of SB2 (column) and SB1 (row); the second begins at the junction of SB1 (column) and SB2 (row). These subdiagonals represent a strong confusion by the computer between two identical bisyllabic words with different accents, suggesting that the effect of emphasis on classification is not large. This result further suggests that the percentage of correct classifications can be materially increased if emphasis is not taken into account by the computer. That is, we can regard confusions of emphasis not as errors, but as correct classifications of responses. For example, the number of total correct responses in the main diagonals for subgroup 101-200 in Tables 11 and 12 are 592 and 527, or 63% and 59%, respectively. By disregarding the confusions of emphasis on the bisyllabic words in classifying responses, these figures increase to 689 and 594, or 76% and 63% correctly classified responses, respectively.

Table 13 is the confusion matrix for the Between Subjects comparison. This shows that although there were sporadic incidences of relatively high correct response classifications in subgroups 101-200 and 1-255 (due to the EMG classification described above), in general the classifications were randomly distributed. Examination of the three confusion matrices in Tables 11, 12, and 13 reveals no consistent confusion of one word with another or one electrode with another.

Time Shift and Amplitude Variation

Two additional sources of error are illustrated in Figure 12. The first, an EMG response to TIP 8, was a slight shifting in time (to the left) of the electrophysiological response with respect to the onset of vocalization. Since the onset of vocalization was taken as the time zero reference, then any such shift would cause an incorrect classification even though the waveform of the individual response is very similar to the template. In this case, TIP 8 was confused with COOL. The second source of error was due to amplitude variation, as shown in an EMG response to TIP 9, so that TIP 9 was also confused with COOL (note that although there was also a time shift in TIP 9, it was shifted relative to both templates).

Another possible source of temporal error is contraction or expansion in time of an individual response with respect to the template. So far, no examples have been found in the raw data, although they may exist. A computer program designed to detect such errors and to correct for them is now being devised.

SUMMARY CONFUSION MATRIX, ALL SUBJECTS, ALL CHANNELS, WITHIN SESSIONS

[illegible]

Table 12

SUMMARY CONFUSION MATRIX, ALL SUBJECTS, ALL CHANNELS, BETWEEN SESSIONS

SUMMARY TABLE, MARCH 7, 1971

COMPARISON BETWEEN SESSIONS FOR THE SAME SUBJECT

SUMMER OVER THE FOLLOWING DATA SETS

A4 DATA WITH M4 TEMPLATES
 A4 DATA WITH M4 TEMPLATES
 C4 DATA WITH C4 TEMPLATES
 C4 DATA WITH C4 TEMPLATES
 D4 DATA WITH D4 TEMPLATES
 D4 DATA WITH D4 TEMPLATES
 1-100.101-200.201-255
 1-100.101-200.201-255
 1-100.101-200.201-255
 1-100.101-200.201-255
 1-100.101-200.201-255
 1-100.101-200.201-255

NUMBER OF REPETITIONS PER WORD

WORD	TIP	HAD	PUT	COOL	MIT	SW1	H41	SW2	BB2	SW2	CD2	MT2
A4	60	60	60	60	60	60	60	60	60	60	60	60

CONFUSION MATRIX

ALL CHANGE DATA, (CATEGORIES 33-34)

SAMPLES 1-100

SAMPLES 101-200

WORD	GETS CLASSIFIED AS IF IT WERE											
	TIP	HAD	PUT	COOL	MIT	SW1	H41	SW2	BB2	SW2	CD2	MT2
TIP	13	7	0	0	0	0	0	0	0	0	0	0
HAD	1	1	1	1	1	1	1	1	1	1	1	1
PUT	0	0	0	0	0	0	0	0	0	0	0	0
COOL	0	0	0	0	0	0	0	0	0	0	0	0
MIT	0	0	0	0	0	0	0	0	0	0	0	0
SW1	0	0	0	0	0	0	0	0	0	0	0	0
H41	0	0	0	0	0	0	0	0	0	0	0	0
SW2	0	0	0	0	0	0	0	0	0	0	0	0
BB2	0	0	0	0	0	0	0	0	0	0	0	0
SW2	0	0	0	0	0	0	0	0	0	0	0	0
CD2	0	0	0	0	0	0	0	0	0	0	0	0
MT2	0	0	0	0	0	0	0	0	0	0	0	0

SAMPLES 201-255

WORD	GETS CLASSIFIED AS IF IT WERE											
	TIP	HAD	PUT	COOL	MIT	SW1	H41	SW2	BB2	SW2	CD2	MT2
TIP	13	7	0	0	0	0	0	0	0	0	0	0
HAD	1	1	1	1	1	1	1	1	1	1	1	1
PUT	0	0	0	0	0	0	0	0	0	0	0	0
COOL	0	0	0	0	0	0	0	0	0	0	0	0
MIT	0	0	0	0	0	0	0	0	0	0	0	0
SW1	0	0	0	0	0	0	0	0	0	0	0	0
H41	0	0	0	0	0	0	0	0	0	0	0	0
SW2	0	0	0	0	0	0	0	0	0	0	0	0
BB2	0	0	0	0	0	0	0	0	0	0	0	0
SW2	0	0	0	0	0	0	0	0	0	0	0	0
CD2	0	0	0	0	0	0	0	0	0	0	0	0
MT2	0	0	0	0	0	0	0	0	0	0	0	0

Table 13

SUMMARY CONFUSION MATRIX, ALL CHANNELS, ALL SUBJECTS, BETWEEN SUBJECTS

SUMMARY TABLES, MARCH 7, 1973

GROUP 3 DATA -- BETWEEN SESSIONS FOR DIFFERENT SUBJECTS

SUMMED OVER THE FOLLOWING DATA SETS

AS DATA WITH C4 TEMPLATES

C4 DATA WITH D3 TEMPLATES

D4 DATA WITH M4 TEMPLATES

NUMBER OF REPETITIONS PER WORD

TIP	MAO	PUT	COOL	MIT	SH1	SH2	SH3	SH4	SH5	SH6	SH7	SH8	SH9	SH10	SH11	SH12	SH13	SH14	SH15	SH16	SH17	SH18	SH19	SH20	SH21	SH22	SH23	SH24	SH25	SH26	SH27	SH28	SH29	SH30	SH31	SH32	SH33	SH34	SH35	SH36	SH37	SH38	SH39	SH40	SH41	SH42	SH43	SH44	SH45	SH46	SH47	SH48	SH49	SH50	SH51	SH52	SH53	SH54	SH55	SH56	SH57	SH58	SH59	SH60	SH61	SH62	SH63	SH64	SH65	SH66	SH67	SH68	SH69	SH70	SH71	SH72	SH73	SH74	SH75	SH76	SH77	SH78	SH79	SH80	SH81	SH82	SH83	SH84	SH85	SH86	SH87	SH88	SH89	SH90	SH91	SH92	SH93	SH94	SH95	SH96	SH97	SH98	SH99	SH100	SH101	SH102	SH103	SH104	SH105	SH106	SH107	SH108	SH109	SH110	SH111	SH112	SH113	SH114	SH115	SH116	SH117	SH118	SH119	SH120	SH121	SH122	SH123	SH124	SH125	SH126	SH127	SH128	SH129	SH130	SH131	SH132	SH133	SH134	SH135	SH136	SH137	SH138	SH139	SH140	SH141	SH142	SH143	SH144	SH145	SH146	SH147	SH148	SH149	SH150	SH151	SH152	SH153	SH154	SH155	SH156	SH157	SH158	SH159	SH160	SH161	SH162	SH163	SH164	SH165	SH166	SH167	SH168	SH169	SH170	SH171	SH172	SH173	SH174	SH175	SH176	SH177	SH178	SH179	SH180	SH181	SH182	SH183	SH184	SH185	SH186	SH187	SH188	SH189	SH190	SH191	SH192	SH193	SH194	SH195	SH196	SH197	SH198	SH199	SH200	SH201	SH202	SH203	SH204	SH205	SH206	SH207	SH208	SH209	SH210	SH211	SH212	SH213	SH214	SH215	SH216	SH217	SH218	SH219	SH220	SH221	SH222	SH223	SH224	SH225	SH226	SH227	SH228	SH229	SH230	SH231	SH232	SH233	SH234	SH235	SH236	SH237	SH238	SH239	SH240	SH241	SH242	SH243	SH244	SH245	SH246	SH247	SH248	SH249	SH250	SH251	SH252	SH253	SH254	SH255	SH256	SH257	SH258	SH259	SH260	SH261	SH262	SH263	SH264	SH265	SH266	SH267	SH268	SH269	SH270	SH271	SH272	SH273	SH274	SH275	SH276	SH277	SH278	SH279	SH280	SH281	SH282	SH283	SH284	SH285	SH286	SH287	SH288	SH289	SH290	SH291	SH292	SH293	SH294	SH295	SH296	SH297	SH298	SH299	SH300	SH301	SH302	SH303	SH304	SH305	SH306	SH307	SH308	SH309	SH310	SH311	SH312	SH313	SH314	SH315	SH316	SH317	SH318	SH319	SH320	SH321	SH322	SH323	SH324	SH325	SH326	SH327	SH328	SH329	SH330	SH331	SH332	SH333	SH334	SH335	SH336	SH337	SH338	SH339	SH340	SH341	SH342	SH343	SH344	SH345	SH346	SH347	SH348	SH349	SH350	SH351	SH352	SH353	SH354	SH355	SH356	SH357	SH358	SH359	SH360	SH361	SH362	SH363	SH364	SH365	SH366	SH367	SH368	SH369	SH370	SH371	SH372	SH373	SH374	SH375	SH376	SH377	SH378	SH379	SH380	SH381	SH382	SH383	SH384	SH385	SH386	SH387	SH388	SH389	SH390	SH391	SH392	SH393	SH394	SH395	SH396	SH397	SH398	SH399	SH400	SH401	SH402	SH403	SH404	SH405	SH406	SH407	SH408	SH409	SH410	SH411	SH412	SH413	SH414	SH415	SH416	SH417	SH418	SH419	SH420	SH421	SH422	SH423	SH424	SH425	SH426	SH427	SH428	SH429	SH430	SH431	SH432	SH433	SH434	SH435	SH436	SH437	SH438	SH439	SH440	SH441	SH442	SH443	SH444	SH445	SH446	SH447	SH448	SH449	SH450	SH451	SH452	SH453	SH454	SH455	SH456	SH457	SH458	SH459	SH460	SH461	SH462	SH463	SH464	SH465	SH466	SH467	SH468	SH469	SH470	SH471	SH472	SH473	SH474	SH475	SH476	SH477	SH478	SH479	SH480	SH481	SH482	SH483	SH484	SH485	SH486	SH487	SH488	SH489	SH490	SH491	SH492	SH493	SH494	SH495	SH496	SH497	SH498	SH499	SH500	SH501	SH502	SH503	SH504	SH505	SH506	SH507	SH508	SH509	SH510	SH511	SH512	SH513	SH514	SH515	SH516	SH517	SH518	SH519	SH520	SH521	SH522	SH523	SH524	SH525	SH526	SH527	SH528	SH529	SH530	SH531	SH532	SH533	SH534	SH535	SH536	SH537	SH538	SH539	SH540	SH541	SH542	SH543	SH544	SH545	SH546	SH547	SH548	SH549	SH550	SH551	SH552	SH553	SH554	SH555	SH556	SH557	SH558	SH559	SH560	SH561	SH562	SH563	SH564	SH565	SH566	SH567	SH568	SH569	SH570	SH571	SH572	SH573	SH574	SH575	SH576	SH577	SH578	SH579	SH580	SH581	SH582	SH583	SH584	SH585	SH586	SH587	SH588	SH589	SH590	SH591	SH592	SH593	SH594	SH595	SH596	SH597	SH598	SH599	SH600	SH601	SH602	SH603	SH604	SH605	SH606	SH607	SH608	SH609	SH610	SH611	SH612	SH613	SH614	SH615	SH616	SH617	SH618	SH619	SH620	SH621	SH622	SH623	SH624	SH625	SH626	SH627	SH628	SH629	SH630	SH631	SH632	SH633	SH634	SH635	SH636	SH637	SH638	SH639	SH640	SH641	SH642	SH643	SH644	SH645	SH646	SH647	SH648	SH649	SH650	SH651	SH652	SH653	SH654	SH655	SH656	SH657	SH658	SH659	SH660	SH661	SH662	SH663	SH664	SH665	SH666	SH667	SH668	SH669	SH670	SH671	SH672	SH673	SH674	SH675	SH676	SH677	SH678	SH679	SH680	SH681	SH682	SH683	SH684	SH685	SH686	SH687	SH688	SH689	SH690	SH691	SH692	SH693	SH694	SH695	SH696	SH697	SH698	SH699	SH700	SH701	SH702	SH703	SH704	SH705	SH706	SH707	SH708	SH709	SH710	SH711	SH712	SH713	SH714	SH715	SH716	SH717	SH718	SH719	SH720	SH721	SH722	SH723	SH724	SH725	SH726	SH727	SH728	SH729	SH730	SH731	SH732	SH733	SH734	SH735	SH736	SH737	SH738	SH739	SH740	SH741	SH742	SH743	SH744	SH745	SH746	SH747	SH748	SH749	SH750	SH751	SH752	SH753	SH754	SH755	SH756	SH757	SH758	SH759	SH760	SH761	SH762	SH763	SH764	SH765	SH766	SH767	SH768	SH769	SH770	SH771	SH772	SH773	SH774	SH775	SH776	SH777	SH778	SH779	SH780	SH781	SH782	SH783	SH784	SH785	SH786	SH787	SH788	SH789	SH790	SH791	SH792	SH793	SH794	SH795	SH796	SH797	SH798	SH799	SH800	SH801	SH802	SH803	SH804	SH805	SH806	SH807	SH808	SH809	SH810	SH811	SH812	SH813	SH814	SH815	SH816	SH817	SH818	SH819	SH820	SH821	SH822	SH823	SH824	SH825	SH826	SH827	SH828	SH829	SH830	SH831	SH832	SH833	SH834	SH835	SH836	SH837	SH838	SH839	SH840	SH841	SH842	SH843	SH844	SH845	SH846	SH847	SH848	SH849	SH850	SH851	SH852	SH853	SH854	SH855	SH856	SH857	SH858	SH859	SH860	SH861	SH862	SH863	SH864	SH865	SH866	SH867	SH868	SH869	SH870	SH871	SH872	SH873	SH874	SH875	SH876	SH877	SH878	SH879	SH880	SH881	SH882	SH883	SH884	SH885	SH886	SH887	SH888	SH889	SH890	SH891	SH892	SH893	SH894	SH895	SH896	SH897	SH898	SH899	SH900	SH901	SH902	SH903	SH904	SH905	SH906	SH907	SH908	SH909	SH910	SH911	SH912	SH913	SH914	SH915	SH916	SH917	SH918	SH919	SH920	SH921	SH922	SH923	SH924	SH925	SH926	SH927	SH928	SH929	SH930	SH931	SH932	SH933	SH934	SH935	SH936	SH937	SH938	SH939	SH940	SH941	SH942	SH943	SH944	SH945	SH946	SH947	SH948	SH949	SH950	SH951	SH952	SH953	SH954	SH955	SH956	SH957	SH958	SH959	SH960	SH961	SH962	SH963	SH964	SH965	SH966	SH967	SH968	SH969	SH970	SH971	SH972	SH973	SH974	SH975	SH976	SH977	SH978	SH979	SH980	SH981	SH982	SH983	SH984	SH985	SH986	SH987	SH988	SH989	SH990	SH991	SH992	SH993	SH994	SH995	SH996	SH997	SH998	SH999	SH1000
TIP	MAO	PUT	COOL	MIT	SH1	SH2	SH3	SH4	SH5	SH6	SH7	SH8	SH9	SH10	SH11	SH12	SH13	SH14	SH15	SH16	SH17	SH18	SH19	SH20	SH21	SH22	SH23	SH24	SH25	SH26	SH27	SH28	SH29	SH30	SH31	SH32	SH33	SH34	SH35	SH36	SH37	SH38	SH39	SH40	SH41	SH42	SH43	SH44	SH45	SH46	SH47	SH48	SH49	SH50	SH51	SH52	SH53	SH54	SH55	SH56	SH57	SH58	SH59	SH60	SH61	SH62	SH63	SH64	SH65	SH66	SH67	SH68	SH69	SH70	SH71	SH72	SH73	SH74	SH75	SH76	SH77	SH78	SH79	SH80	SH81	SH82	SH83	SH84	SH85	SH86	SH87	SH88	SH89	SH90	SH91	SH92	SH93	SH94	SH95	SH96	SH97	SH98	SH99	SH100	SH101	SH102	SH103	SH104	SH105	SH106	SH107	SH108	SH109	SH110	SH111	SH112	SH113	SH114	SH115	SH116	SH117	SH118	SH119	SH120	SH121	SH122	SH123	SH124	SH125	SH126	SH127	SH128	SH129	SH130	SH131	SH132	SH133	SH134	SH135	SH136	SH137	SH138	SH139	SH140	SH141	SH142	SH143	SH144	SH145	SH146	SH147	SH148	SH149	SH150	SH151	SH152	SH153	SH154	SH155	SH156	SH157	SH158	SH159	SH160	SH161	SH162	SH163	SH164	SH165	SH166	SH167	SH168	SH169	SH170	SH171	SH172	SH173	SH174	SH175	SH176	SH177	SH178	SH179	SH180	SH181	SH182	SH183	SH184	SH185	SH186	SH187	SH188	SH189	SH190	SH191	SH192	SH193	SH194	SH195	SH196	SH197	SH198	SH199	SH200	SH201	SH202	SH203	SH204	SH205	SH206	SH207	SH208	SH209	SH210	SH211	SH212	SH213	SH214	SH215	SH216	SH217	SH218	SH219	SH220	SH221	SH222	SH223	SH224	SH225	SH226	SH227	SH228	SH229	SH230	SH231	SH232	SH233	SH234	SH235																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																													

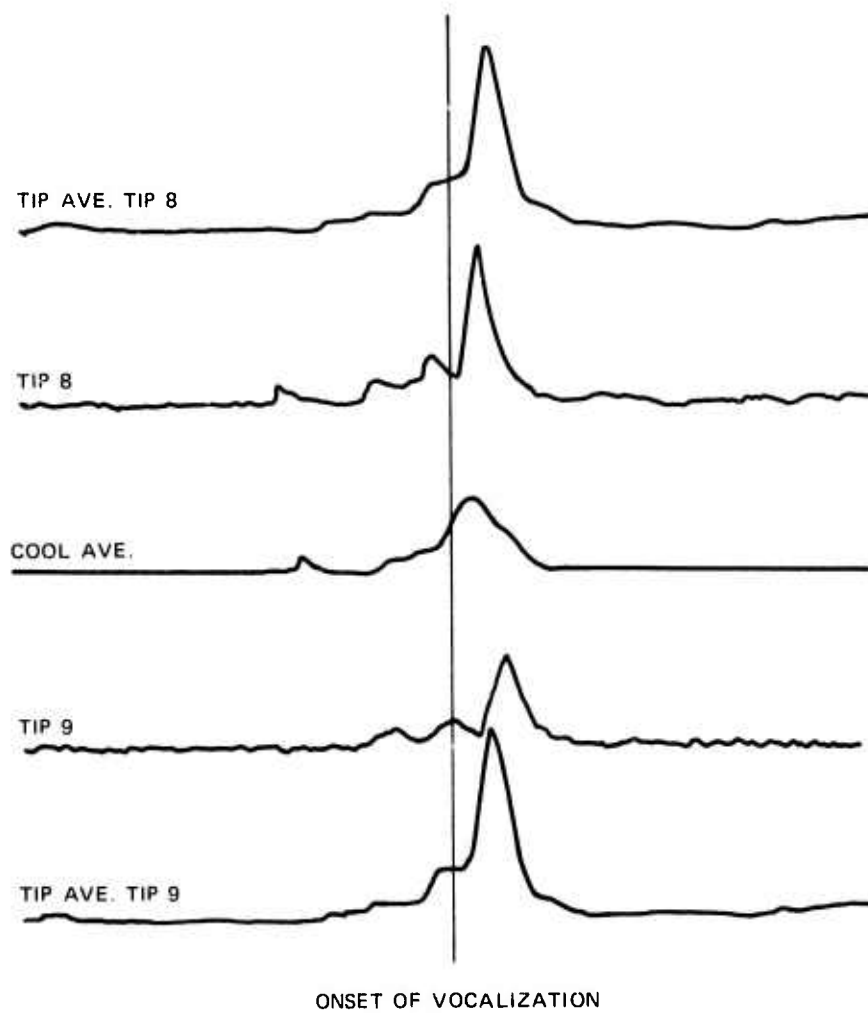


FIGURE 12 TWO EMG RESPONSES (ELECTRODE 13/16, SUBJECT C5) TO TIP
CONFUSED WITH COOL DUE TO TIME SHIFT AND AMPLITUDE
VARIATION

Artifacts

By definition, artifacts are: (1) potentials causing a disturbance not methodically related to the original biological response being measured; or (2) potentials that are methodically related to the response from a source other than that which is assumed to produce the response. The former disturbances are random and cannot contribute to computer recognition of the response, although they can degrade the recognition as random noise. The latter are true consistent disturbances and imply that a particular assumption about the physiological origin of the response is incorrect. However, from a practical point of view, if the computer can recognize the biological response produced by any source, including one whose origin may be mistaken, then bio-cybernetic communication may still function adequately even though all the sources of the response cannot be identified. Several such artifacts are discussed below.

Muscle artifacts were controlled by having Ss relax as much as possible throughout the experimental trials, with the allowance to move around between trials. Examination of the temporal changes of EMG records in comparison with any muscle artifacts in the EEG revealed little contamination from this source.

Figure 13 illustrates a relatively rare occurrence of EMG artifact, in which an EMG response (electrode 7/8) to TIP 1 was classified as MOUSETRAP. The artifact itself is due to a larger voltage response than usual for the amplifier gain, resulting in saturation. The response was misclassified simply because the minimum RMS difference was obtained, by chance, with MOUSETRAP, even though the signal value more closely resembles the form of the TIP template. The confusion has no other significance.

One of the more prevalent artifacts in EEG data is the corneal-retinal-occipital potential due to eye movements. In reading the stimulus words used in this project, such eye movements are practically impossible to eliminate completely. Nevertheless, their contribution may be assessed in various ways. For example, in the collection of Group I data, two stimulus inputs (visual and auditory) were used. In the visual input, both overt and covert responses were obtained to assess the contribution of EMG artifacts caused by speech (overt response). During the auditory input, responses were obtained during eyes open and eyes closed conditions to assess both the contribution of visually evoked responses and eye movements, both presumably absent under these conditions. Results showed that under all four conditions, certain potential changes were present in the EEG that could only be interpreted as true EEG potentials related to verbal behavior (overt or covert), and not attributable to auditory or visually evoked potentials, muscle or movement artifacts, or eye movements (see Figures 3, 4, 5, and 6 of the First Semi-Annual Technical Progress Report and the discussion regarding artifacts on pages 13-19 of that report).

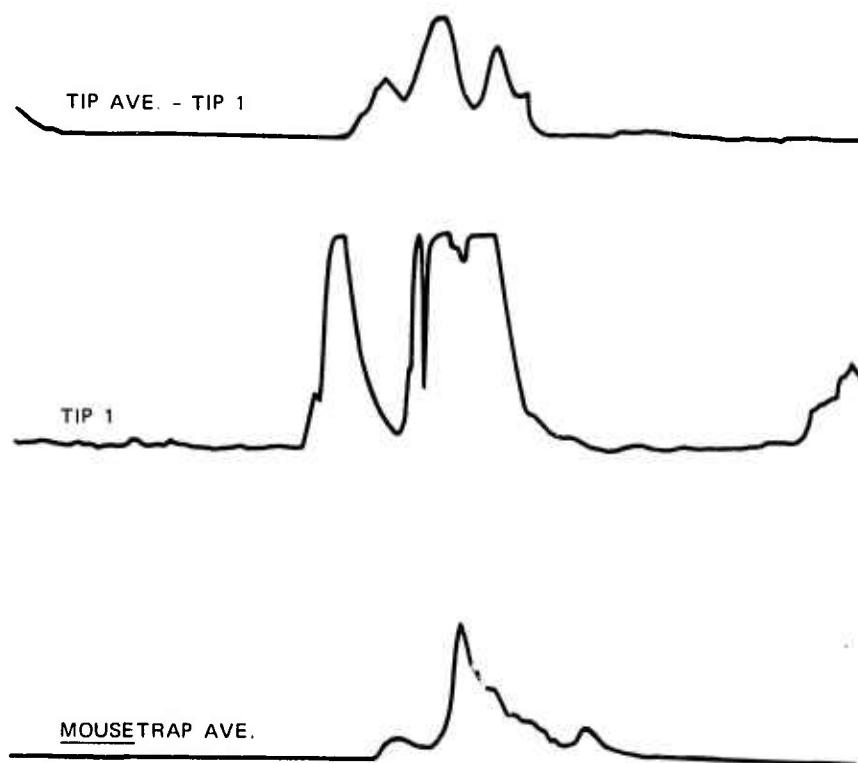


FIGURE 13 MISCLASSIFICATION OF EMG RESPONSE (ELECTRODE 7/8, SUBJECT C5)
DUE TO AMPLIFIER SATURATION

Nevertheless, we cannot know from that data what contribution eye movements may have made to the current data. Therefore, a control study using five words from Table 1 was conducted, where eye movements per se were measured along with the EEG. Six types of stimulus-response combinations were obtained for each of the five words, each repeated five times. The words were TIP, HAD, PUT, COUGHDROP, and SCHOOLBOY. The conditions were:

- (1) Visual stimulus presentation, overt response, eyes open.
- (2) Visual stimulus presentation, covert response (silent reading), eyes open.
- (3) Auditory stimulus presentation, overt response, eyes open.
- (4) Auditory stimulus presentation, covert response, eyes open.
- (5) Auditory stimulus presentation, overt response, eyes closed.
- (6) Auditory stimulus presentation, covert response, eyes closed.

The S was instructed to remain as relaxed as possible between and during trials. On hearing a warning click (CLK) in her earphones for eyes open conditions, S was to fixate on a spot in the center of the stimulus screen. A visual or auditory stimulus was presented 1 sec later, followed in 1 sec by another CLK. On hearing the second CLK, the S was to respond either overtly or covertly according to the condition. Approximately 30 sec later, the next trial began, with a rest of 2 min between conditions. In all trials, eye movements were detected by two pairs of electro-oculograph (EOG) electrodes (one pair for vertical movement, one pair for horizontal) placed around the eyes.

The results may be summarized as follows:

- (1) For the 25 visual stimuli, overt response (worse case for eye movements), eye movements were detected on both the EOG and the four EEG channels when S attended to the fixation point on hearing the warning CLK.
- (2) Of these 25 presentations, nine (38%) had eye movement artifacts in the EEG record as confirmed by the EOG electrodes. Of these nine, only four could be associated with the actual response period; the remainder were randomly distributed. Thus, only 16% of the eye movement artifacts could have contributed to a correct classification, if all of the artifacts occurred in the same way for a given word, which they did not.
- (3) For all other conditions, the amount of eye movement artifacts decreased so that by condition six (auditory stimulus, eyes closed, covert response), no artifacts were obtained at all.

- (4) In all of the records, even those containing a fair amount of artifacts and those containing no artifacts, a specific potential change in the EEG was identifiable in the raw record that could be related to the verbal behavior, whether overtly or covertly produced. In many instances, this potential change had the time course and waveform of those often seen as eye movement artifacts, even when the EOG electrodes showed that no eye movements occurred and even when the response was covert (and therefore was not due to EMG or other jaw movement artifacts). Although artifacts of some sort, such as subvocal tongue movements, cannot be completely ruled out, the probability is high that the potentials we claim to be EEG signals are indeed EEG signals.

Figures 14 and 15 illustrate some of these results for Subject B. Figure 14 illustrates an (A) overt and (B) covert response to the visual stimulus SCHOOLBOY, under conditions of no eye movement artifacts of significance during the response period. The top two channels are the vertical and horizontal EOG electrodes; the next four are the four EEG channels; the last is the CLK code and voice channel. Note that there are definite EOG potentials and artifacts in the EEG in Figure 14A following the first CLK when Subject B attends to the fixation point. Preceding the onset of vocalization, a definite slow-wave negative-positive shift is obtained in the EEG that continues during vocalization. This slow-wave is also seen during the covert response in Figure 14B. This potential is evidently the patterned EEG change (more obvious in electrode F7 and T5) associated with SCHOOLBOY, whether overtly or covertly produced. In Figure 14A and B, there is a small EOG deflection on the horizontal electrode (channel 2) during portions of the vocalization and presumed silent reading. However, since it is not of significant size in either the overt or the covert response, and lasts only during a small portion of either the EEG response or the actual vocalization, it cannot contribute much either as an artifact or in response classification.

In contrast, Figure 15 shows the same overt and covert responses to SCHOOLBOY but, in both cases, accompanied by marked eye movement artifact as confirmed by the EOG electrodes. Note that in the overt responses (Figure 15A), the eye movements occur variably throughout the recording period, not just in association with the verbal response. Thus, they are more likely to produce confusion during classification than aid in classification. However, during vocalization, the EEG response of F7 and T5 which was seen in Figure 14A and B is clearly discernible in Figure 15A and to a reduced extent in Figure 15B (covert response), and is not associated with a particular EOG deflection. This suggests that if response classification were only carried out on the period from about 1 sec before vocalization for about 1.0 to 1.5 sec (corresponding to our best subgroup classifier of sample points 101-200), the response in 15A would be correctly classified despite the artifact.

In addition to the above results with eye movement artifacts, the following points show, on logical grounds, that eye movement artifacts

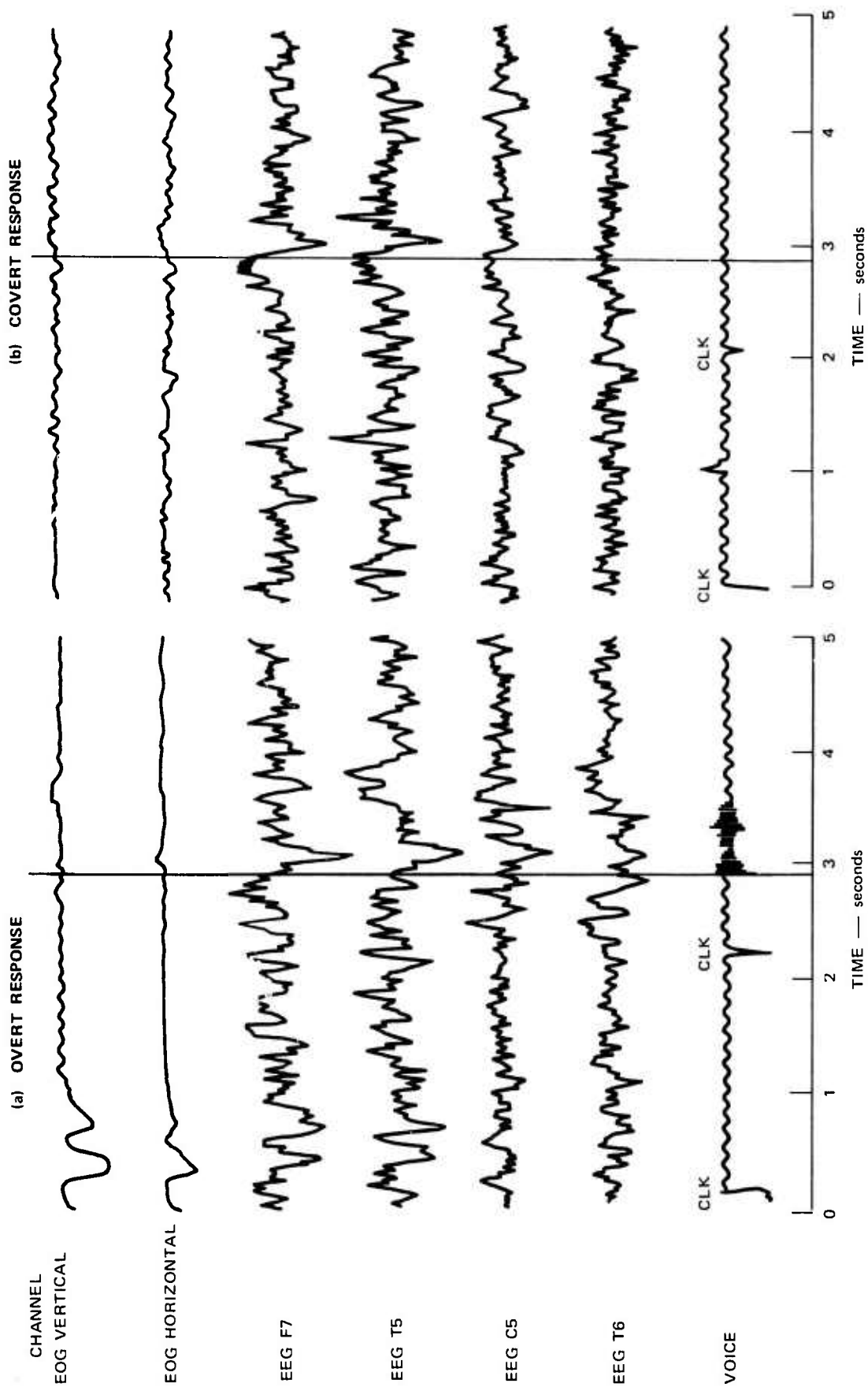


FIGURE 14 EEG IN ABSENCE OF EYE MOVEMENTS, OVERT AND COVERT VERBAL RESPONSE TO SCHOOLBOY, SUBJECT B7

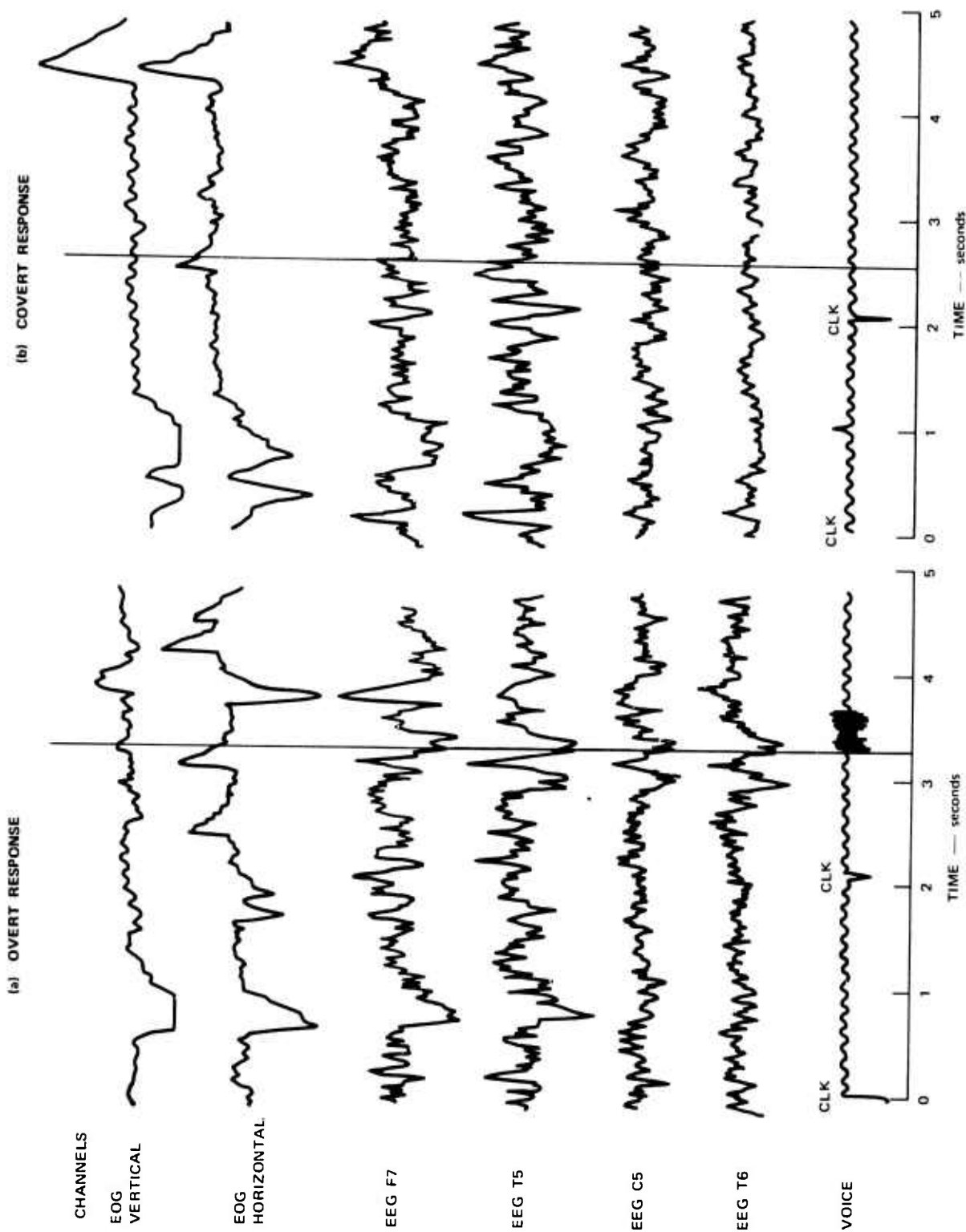


FIGURE 15 EEG IN PRESENCE OF EYE MOVEMENTS, OVERT AND COVERT VERBAL RESPONSE TO SCHOOLBOY, SUBJECT B7

did not contribute significantly to correct computer classifications in this project (although they may well have contributed to confusion).

- (1) Figure 16 shows the EEG templates (electrode F7) for Subject C, Session 5, channel 3, for the words TIP and COOL. It also shows, between the templates, three individual EEG TIP responses on channel 3 that were confused with COOL. It appears that all three--TIP 2, TIP 3, and TIP 4--were probably confused with COOL because of a time shift in their responses to the right (see "cursor") with respect to the TIP template that made their slow-wave responses more coincident with the slow-wave of COOL than with TIP.
- (2) Eye movement artifacts, when they occur, produce a fair amount of variability during a given response period (Figure 15A) and between response periods. Therefore, this variability should show up on the averaged records. Yet, in Figure 11, the variability of the EEG is less than with EMG, a result that is inconsistent with the idea of eye movement artifacts contaminating the record.
- (3) Eye movement artifacts, when they occur, take place when the light stimulus first goes on and the S attends to the stimulus screen as in Figure 14A (over 1 sec before the actual response of the S). Therefore, if eye movement artifacts are present in our templates in a consistent way, then the artifacts occurring at the onset of stimulation should be present in the averaged records; yet nothing of this sort is seen in the majority of templates (e.g., Figures 10 and 11).
- (4) If eye movement artifacts are contributing significantly to correct classification of the EEG response, then a greater consistency would be expected between EEG channels in their percentage of correct classification than was found. That is, we should expect the eye movement artifacts to be consistent on a given channel if they contribute to computer classification. In this case, all EEG channels should classify equally well. However, this was not true; some EEG channels proved to be better classifiers than others (though not in any consistent way across, between, or within Ss).

In any event, in Group III experiments (see Discussion, below), we will attempt to increase response classification performance by removing as many of these errors as possible, and to assess the contributions to success or failure of those that cannot be removed.

Classification by Other Statistics

In addition to the average template comparisons described above, several other statistics were also calculated for Subject C, Session .

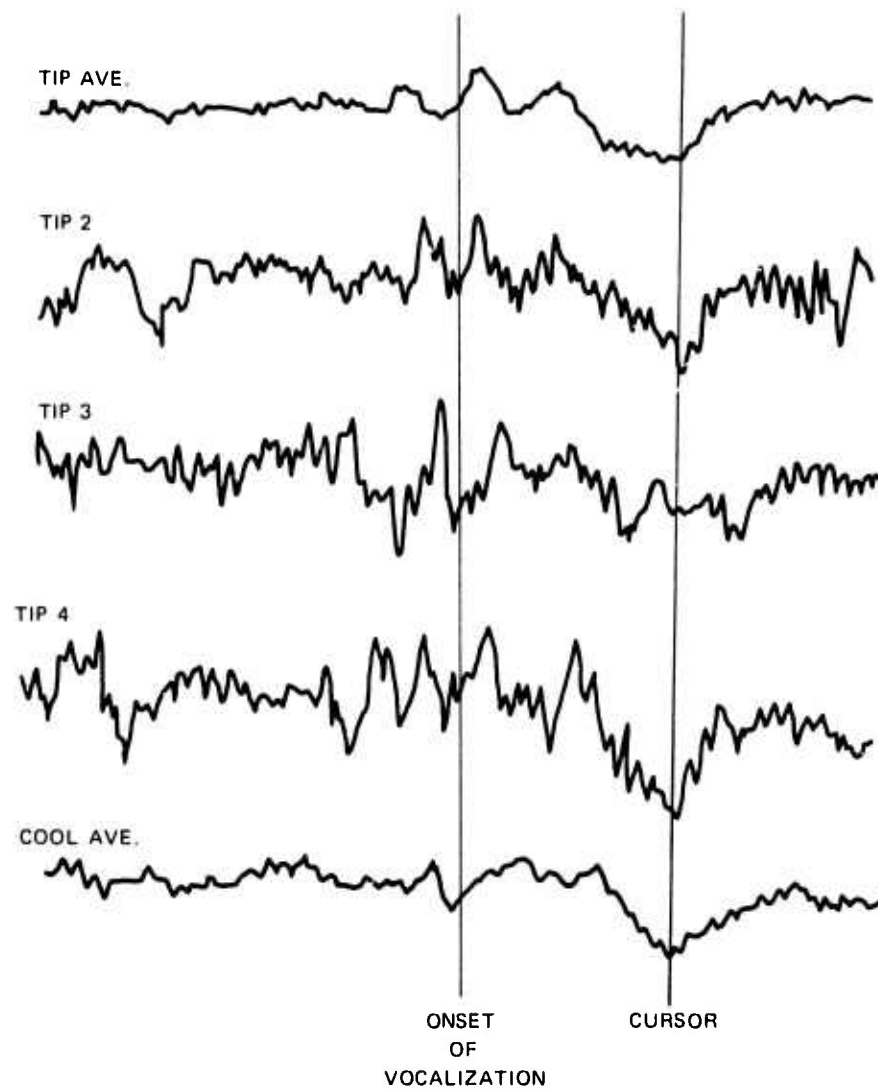


FIGURE 16 THREE EEG RESPONSES (ELECTRODE F7, SUBJECT C5) TO TIP
CONFUSED WITH COOL DUE TO TIME SHIFT

including linear coherence (Coh), weighted-average coherence (Ave Coh), and spectral densities (Freq) for auto- and cross-spectra (see the Appendix for rationale and equations). The results were uniformly disappointing as follows:

<u>Channels</u>	Correct Responses per 150		
	<u>Statistic</u>		
	<u>Coh</u>	<u>Ave Coh</u>	<u>Freq</u>
Both EMG	31	14	34
All EEG	17	10	8
All Electrodes	25	17	16

Because of these results on Subject C, these statistics were not calculated for the other two Ss.

Since all three statistics are based on frequency analysis, we suspect that these low correct classification scores are due, partly at least, to differences in phase which were not taken into account in calculating these statistics. We will correct for phase differences in analyzing the Group III data (see Discussion).

One finding in the spectral density plots, at least for Subject C, was that more alpha activity occurred in the nondominant right hemisphere (EEG T6) than in the homologous electrode (EEG T5) over the dominant (speech) hemisphere. Since, in this S, T6 (nondominant) responses were the poorest EEG classifiers and T5 responses were the best EEG classifiers, then this alpha difference may be related to the variability in the two templates for response classification. This will be further examined during collection and analysis of Group III data.

DISCUSSION AND CONCLUSIONS

Significance of Results

(1) For all three Ss tested, a high percentage of individual word utterances were correctly classified, based only on machine recognition of biological signals. There was some variability in this capacity. Within each S, the second session had a higher rate of correct classifications than the first, indicating a learning or habituation effect that probably reduced the response variability. There were also differences among Ss, due to differences in the variability among them, with the responses of Subject C classifying more correctly than either B or D. Nevertheless, for all three Ss, variability in their individual templates was relatively low, and the rate of correct classifications was high--generally over 50%. The numbers correctly classified were significant with a probability well below .001 that this occurred by chance.

(2) The greatest variability within Ss was between types of biological recordings. EMG responses were almost twice as good as classifiers as were FEG responses, although the two taken together were better than either group (or individual electrodes within a group) alone. This finding suggests that more than one electrode should be used in a biocybernetic communication system. It is supported by the result that there was no evidence in any of the Ss that a given electrode of either the EMG or EEG groups was consistently better as a classifier than any other electrode in the group. One exception to this, however, is that in homologous EEG electrodes T5 and T6, in Subjects C and D, T5 was a predominantly better classifier than was T6, while in Subject B the opposite was true. This finding is possibly related to the results from the spectral analysis in Subject C, that T6 contained consistently higher amplitudes of alpha frequencies than T5.

(3) Another source of variability, shown by the F-ratios, was the part of the biological response analyzed. It is evident that if only that portion of the biological response associated with the actual verbal response is used, then the rate of correct classification increases. This may actually be easier to do with continuous speech (or thought) than single words, since variability with single words is greatest between words.

(4) As expected from Group I results, each S's biological responses associated with speech are unique to him, as confirmed by the Between Subjects results. It is of scientific interest that a fair number of EMG responses were significantly classified correctly between Ss, indicating that muscle activity for verbal expression may be more invariant between individuals than has been supposed (MacNeilage and MacNeilage, 1971).

This result also means, however, that unique templates must be built for each individual using a biocybernetic communication system.

(5) A surprising result from the confusion matrices was the finding that emphasis on different parts of the bisyllabic words did not materially effect biological responses. This should reduce possible future problems, since the library of templates in a biocybernetic communication system may be reduced to tolerable dimensions if emphasis on all accented words can be ignored.

(6) One additional source of error identified in our results may be eliminated by additional computer processing, while two others may not be eliminated at all. The first is the time shift in a biological response with respect to the onset of vocalization (or verbal thinking) from one response to another. We do not know how many errors occurred due to this shifting, but the error can be removed by time justification using a minimum difference criteria between two responses before combining them to make a template, and before calculating an RMS difference for classification. This will be done on Group III data.

(7) The other two errors we may have to accept--namely, amplitude and movement artifacts. The first of these may possibly be corrected for by an automatic gain-change feature in biocybernetic amplifiers, or by identification through context, or both. The second of these, and especially eye movement artifacts, may be reduced when speech (or thought) is continuous, by time shifting or by closing the eyes. We are confident from the results of our control study that eye movements did not overly contaminate our records to reduce classification rate, and certainly were not the major EEG parameter that contributed to correct classification (despite the fact that parts of some of the EEG averages look like artifact).

To conclude, we believe that the results of this year's research, and particularly the results reported herein, have demonstrated beyond our expectations that a biocybernetic communication system using biological information related to speech is definitely feasible. During the next year, we expect to find out if it is also feasible for verbal thinking.

Future Research--Group III Data

Details of the work to be conducted in the second contract year are in SRI Proposal No. LSU 72-133, dated October 30, 1972. In the light of the present results, it would be useful to list the specific objectives.

- (1) Biologic response measurements will be made over shorter intervals of time to correspond with verbal (overt and covert) responses.

- (2) Instrumentation will be used to monitor all types of artifacts. Samples containing artifacts of any sort will be divided into subgroups according to type, and classified separately to assess the contribution of artifact-rich relative to artifact-poor measures.
- (3) All other sources of error described above will be eliminated as nearly as possible.
- (4) Attempts will be made to identify the smallest unit of speech that can be correctly classified with a minimum template vocabulary or library.
- (5) An effort will be made to assess the contributions of the EEG from dominant and nondominant speech areas of the brain to correct classification.
- (6) An attempt will be made to identify the various components of a biological response related to overt and covert speech, including mechanical, semantic, contextual, and affective components.
- (7) Finally, and most important, we will primarily attempt to classify covert verbal behavior, or thinking, with biological signals alone.

Appendix

DISCUSSION OF STATISTICS USED FOR MACHINE RECOGNITION

To classify the words in the test vocabulary automatically, it is necessary to have both a procedure of combining the data from the measurements and a statistic whose numerical value determines the final classification. Several statistics have been tried in this project, and the formal mathematical definitions for each are given below.

Introduction and Terminology

We believe that it is helpful to clarify some basic facts about the recognition process in general, before describing our particular recognition application using bioelectric potentials. The purpose of all our statistics is to enable accurate recognition so that the signals can be used for biocybernetic communication purposes. The two main approaches used are template matching based, first, on the pattern of the signal over time, and second, on the pattern over frequency of the power spectral density function of the signal. Recognition allows us great economy in biocybernetic communication because we may substitute the label or recognition category for the signal itself.

"Recognition" means the labeling of some measurement data according to pre-established criteria or boundaries. In our case, we use the names of the words themselves--e.g., HAD, PUT, and so on--as the labels for groups of measurements that were taken when the subject was saying these words. Recognition requires such labels to be supplied, whereas clustering does not. "Clustering" means the partitioning of all the measurements into self-consistent or homogeneous groups, without reference to

any preconceived labels. Clustering handles the measurements as they are, whereas recognition fits the measurements to external labels. A clustering method finds an appropriate number of valid groups so that the clustering is an accurate but abbreviated description (summary or template) of the data. Clustering facilitates recognition usually by providing a rational objective method of labeling the measurements. The recognition labels may be rather arbitrary and not logically related to the measurements, except by convention, established practice, or preference.

"Spectral Analysis" is a method of decomposing any time waveform into a set of sinusoidal waves that can be combined to reconstruct the original waveform. There are two kinds of spectral analysis: the usual kind, which we have used, which ignores the phase of the frequency components, and a more sophisticated kind, called complex spectral analysis, which gives phase information as well. We will discuss only the first kind here. In future work, we will apply a spectral analysis program that will take phase into account (Singleton, 1967). The purpose of spectral analysis is to transform the waveform or time description of a signal into a frequency description in the hope that recognition of the signal can be made, assuming the frequency description corresponds more closely to the recognition requirements than does the time description.

Clustering Approach to Recognition

It had been our original intention to apply the clustering program ISODATA to the data. The computation time for one iteration through the data for this program is given approximately by the following formula:

$$T = NCOLS \times NROWS \times NPATS \times M \text{ seconds}$$

where

NCOLS = the number of variables (columns)

NROWS = the number of clusters (rows)

NPATS = the number of patterns

M = a factor depending on the basic cycle-time of the computer.

In the case of Group II data, there are 15 words, so we can hopefully find 15 clusters--one cluster for each word. By evaluating NCOLS, NROWS, and NPATS and estimating a value for M, it was found that the computation time and the computer memory size required were rather large for this project. Thus, to save computation time necessary for the iterative searching procedure of ISODATA, and because we would have had to modify the program to expand its memory requirements to accommodate the large number of data samples, we economized on computation expenses by writing a noniterative, special-purpose "clustering" program for this particular application. Because the data are sufficiently well-clustered, this approach is satisfactory at the 15-cluster level, so the usual iterative search procedure was not necessary, and templates formed from averages of the data in each category were used as the cluster center.

Let $X_{st\ ijk\ell}$ be a basic data value for

subject s , $s = B, C, \text{ or } D$

session t , $t = 1 \text{ or } 2$

time i , $1 \leq i \leq 255$

channel j , $1 \leq j \leq 6$

word category k , $1 \leq k \leq 15$

repetition ℓ , $1 \leq \ell \leq 10$.

The data were digitized to 9 bits accuracy, so $-255 \leq X_{st\ ijk\ell} \leq 255$ for all i, j, k, ℓ, s , and t as above.

The template or average value is computed by averaging (Clynes et al., 1967) each point in the ten responses (i.e., repetitions) within a known word category (k). Thus, for any word category k,

$$st_{ijk}^A = \frac{1}{10} \sum_{\ell=1}^{10} st_{ijk\ell}^X \quad .$$

The RMS difference ($R_{c k\ell m}$) between the ℓ th utterance of word k and the template for word category m ($1 \leq m \leq 15$), where c denotes the combination of time samples and channels, is given by:

$$R_{c k\ell m} = \sqrt{\frac{1}{N_c} \sum_{i \in c} \sum_{j \in c} \left(s_1 t_1 X_{ijk\ell} - s_2 t_2 A_{ijm}^* \right)^2}$$

where N_c is the number of data points in combination c and

$$s_2 t_2 A_{ijm}^* = \begin{cases} s_2 t_2 A_{ijm} & \text{if } s_1 \neq s_2 \text{ or } t_1 \neq t_2 \text{ or } m \neq k \\ \text{or} \\ \frac{10}{9} s_1 t_1 A_{ijk} - s_1 t_1 X_{ijk\ell} & \text{if } s_1 = s_2 \text{ and } t_1 = t_2 \text{ and } m = k \end{cases} .$$

F-Ratio Test for Significance of Variance Between and Within Templates

An F-statistic was calculated for each point in time for each channel and for each session, and a plot was made of each F-value versus time.

Let $F_{st\ ij}$ be a F value at

time $i, 1 \leq i \leq 255$
channel $j, 1 \leq j \leq 6$
subject $s, s = B, C, \text{ or } D$
session $t, t = 1 \text{ or } 2$

then

$$F_{st\ ij} = \frac{st\ SSB_{ij} / (15 - 1)}{st\ SSW_{ij} / [15(10 - 1)]}$$

where

$st\ SSB_{ij}$ = sum of squares between templates

$st\ SSW_{ij}$ = sum of squares within templates

$15 - 1 = 14$ = degrees of freedom in numerator

$15(10 - 1) = 135$ = degrees of freedom in denominator.

$$st\ SSB_{ij} = \frac{1}{10} \left\{ \sum_{k=1}^{15} \left(\sum_{\ell=1}^{10} st\ X_{ijk\ell} \right)^2 - \frac{1}{15} \left[\sum_{k=1}^{15} \left(\sum_{\ell=1}^{10} st\ X_{ijk\ell} \right) \right]^2 \right\}$$

$$st\ SSW_{ij} = \sum_{k=1}^{15} \left[\left(\sum_{\ell=1}^{10} st\ X_{ijk\ell} \right)^2 - \frac{1}{10} \left(\sum_{\ell=1}^{10} st\ X_{ijk\ell} \right)^2 \right]$$

where $X_{st\ ijk\ell}$ is the same as previously defined.

From a table of the F-statistic (Selby, 1971), values greater than 1.77 are significant at the .05 level, and values above 2.23 are significant at the .01 level. In most cases, the F-statistic showed that the time segment over which the classification was significant was from the middle subgroup samples 101-200.

Combinations of Data Points and Channels

Based on the results with the F-ratio test, various combinations of points in time and various channels (electrode placements) were used to explore time segments and electrode placements to determine which combinations would give the highest correct identification of the words. The samples in time were divided into subgroups--i.e., samples 1-100 being the first subgroup, samples 101-200 the second subgroup (where the F-ratios were significant), and 201-255 the final subgroup. In addition, all samples (1-255) were used, giving four groups of time points.

All six channels were treated individually. In addition, EMG channels (1 and 2) were grouped together, EEG channels (3, 4, 5, and 6) were grouped together, and finally all channels were grouped together, giving nine different channel combinations.

Thus, with the four time segments there were 36 different channel-time combinations. Typical values of N_c (used in calculating the RMS difference) are:

<u>Combination</u>	<u>N_c</u>
Channel 1, samples 101-200	100
EMG (Channels 1 and 2), all samples	510
All channels, all samples	1530

Closest-Match Recognition and Confusion Matrix

The recognition or classification of each test word was accomplished by matching it to the set of all templates. The best match is word w where

$$R_{c\ k\ell w} = \min_{m=1}^{m=15} \left\{ R_{c\ k\ell 1}, R_{c\ k\ell 2}, \dots, R_{c\ k\ell m}, \dots, R_{c\ k\ell 15} \right\} \text{ occurs.}$$

If $w = k$ for the minimum value, this is considered a correct match; if $w \neq k$, an incorrect match was found.

A confusion matrix (C_{kw}) was computed as the table for the number of times word k was classified as being word w . Matrices were formed for each combination of time samples and channels. The main diagonal (where $k = w$) gives a tally of the number of correct matches for each word. A chi-square statistic was calculated based on these correct matches to test for significance (nonrandomness).

The Chi-Square Test of Significance

As there are 15 different words, the probability of picking a particular word correctly by chance is $1/15$. There are ten repetitions of each word, giving $10/15$ as the expected number of correct responses assuming random data.

Two chi-square statistics were computed: (1) a chi-square with 15 degrees of freedom, which tests significance of recognition of the 15 words; and (2) a chi-square with 1 degree of freedom, which tests the significance of the total number of responses correctly classified, summed over all words.

Let C_{kw} be the general element of the confusion matrix, as defined earlier--i.e., C_{kw} is the number of times word k gets classified as if it were word w . Let χ^2_1 be the chi-square statistic with 1 degree of freedom, and χ^2_{15} be the chi-square statistic with 15 degrees of freedom. Then, for one session,

$$\chi^2_1 = \frac{\left(\sum_{i=1}^{15} c_{ii} - \frac{150}{15} \right)^2}{\frac{(15 - 1)}{15 \cdot 15} (150)}$$

$$\chi^2_{15} = \frac{\sum_{i=1}^{15} \left(c_{ii} - \frac{10}{15} \right)^2}{\frac{(15 - 1)}{15 \cdot 15} (10)}$$

Critical values for rejection of the hypothesis of no significant difference between the observed sample and a random population were 6.64, $p \leq .01$, for 1 degree of freedom, and 30.58, $p \leq .01$, for 15 degrees of freedom.

Spectral Analysis Using the Fast Fourier Transform

The method of transforming a waveform in the time domain to a mathematically equivalent representation in the frequency domain is known as a "Fourier transformation." The computational implementation of this transform on a computer is called a "fast" transform, because a particular algorithm is required to make such computations efficient. For this project, we used a computer program supplied to us by one of our project consultants, Dr. Gary Galbraith. This program came from the Biomedical Data (BMD) series developed at UCLA, was adapted by Galbraith for his computer, and then readapted by Wolf for the SRI CDC-6400. Galbraith first used a spectral analysis program that is documented (Dixon, 1970) as BMD02T "Autocovariance and Power Spectral Analysis." After gaining experience with this particular program, Galbraith updated his approach to the newer version in the same series, which is cataloged as 91 x FF.

Although the mathematics of Fourier transformation is readily available from many sources, an outline of the mathematical fundamentals is presented below because we wish to develop an exposition of this approach for comparison to the clustering approach that we find more effective in this application. A single frequency, or a pure spectral line, is given by

$$s_n(t) = A_n \cos \left(2\pi \frac{nt}{T} - \phi_n \right)$$

and is represented in Figure 17. The peak amplitude is A_n , and the phase angle with respect to the origin is ϕ_n . It is important to note that the time variable is assumed to extend from $-\infty$ to $+\infty$; although this is unrealistic for actual signals, it is convenient mathematically. Actual biological signals, such as the EMG and EEG waveforms measured in this project, may be considered to be mathematically composed of a summation of such sinusoidal signals. By using enough harmonics, any limited bandwidth periodic signal can be represented by the composition of a number of sinusoidal (i.e., purely periodic) signals only.

We may thus represent any periodic waveform by

$$s(t) = \sum_n A_n \cos \left(2\pi \frac{nt}{T} - \phi_n \right) .$$

The quantities A_n are the spectra (or spectral amplitudes) and are given by the computer program output. The program has been calibrated by means of a test signal recorded by using a signal generator of known (calibrated) frequency.

The source listing of the computer program for spectral analysis consists of two pages of FORTRAN and several subroutines as listed below.

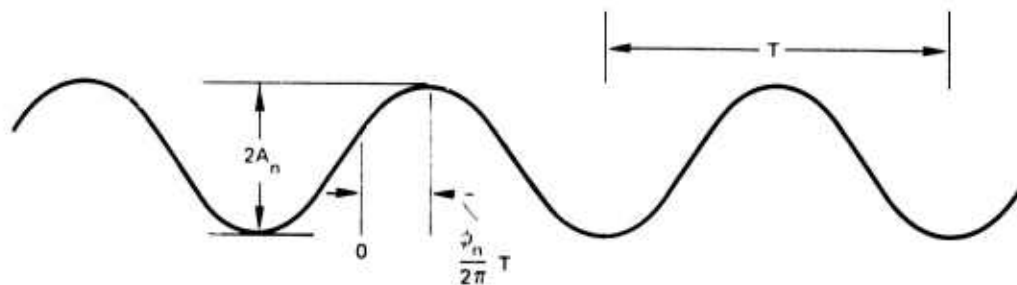


FIGURE 17 DEFINITION OF TERMS FOR FOURIER ANALYSIS

<u>Name</u>	<u>Lines of FORTRAN</u>	<u>Purpose</u>
GARY	97	MAIN PROGRAM, READS TAPE, APPLIES WINDOW
FAST	50	COMPUTES SPECTRA
PRT	23	PRINTS VALUES
XBAR	72	COMPUTES AVERAGE COHERENCE

The output of the program first lists the description of the data on the tape such as the subject's number and date of recording. Next, the coherence (as defined below) between all possible pairs of channels is given for each of the 33 bins of the frequency spectrum we employed (0 to 19 Hz). Since we used six channels, there are $\binom{6}{2} = 15$ different combinations of channels taken two at a time for cross-spectral amplitudes, and six auto-spectral amplitudes, making a total of 21. Similarly for the quantity \bar{C} , there are another 21 values for each of the bins.

The Coherence and Weighted-Average Coherence Statistics

"Linear coherence" is a statistic that provides an estimate of the degree to which a particular frequency component in the EEG of one brain region is related to an identical frequency component in the EEG of another brain region. Thus, in a cross-spectral analysis as many coherence values may be calculated as there are frequency bins (Walter, 1963). The "weighted-average coherence," on the other hand, is a statistic derived from cross-spectral frequency analysis parameters that, in a sense, summarize over the several linear coherences in a cross-spectrum to give a single number that measures the overall degree of interaction between two brain regions (Galbraith, 1967). The term "weighted" refers to the fact that the EEG of the two regions used in computation must be large in amplitude and highly coherent.

Following Galbraith (1966, 1967) we define the coherence function, at frequency f , as

$$C(f) = A_{xy}(f) / [A_x(f) A_y(f)]^{1/2}$$

where

A_{xy} is the cross-spectral density

A_x is the autospectral density of Channel x

A_y is the autospectral density of Channel y.

$C(f)$ is normalized and bounded between 0.0 (Complete lack of relationship) and 1.0 (perfect linear relationship).

The weighted average coherence function is defined by

$$\bar{C} = \sum_i [A_{xy}(f_i) C(f_i)] / \sum_i A_{xy}(f_i)$$

where

$A_{xy}(f_i)$ is the cross-spectral density at frequencies f_i satisfying a threshold criterion that they must exceed.

$C(f_i)$ is the coherence at frequency f_i satisfying the threshold criterion.

The computer program prints out these quantities, which we later used as input to the template matching program, in place of the original time series data. The use of these spectral data or coherence statistics did not provide as good recognition results as obtained with the original waveform data.

REFERENCES

- Adey, W. R., Kado, R. T., and Walter, D. O. Computer analysis of EEG data from Gemini flight GT-7. *Aerospace Medicine* 38(4), 345-359, 1967.
- Clynes, M., Kohn, M., and Gradijan, J. Computer recognition of the brain's visual perception through learning the brain's physiologic language. 1967 IEEE International Convention Record, Pt. 9, 125-142, New York, March 20-23, 1967.
- Dixon, W. J. (ed.). BMD Biomedical Computer Programs, University of California Publications in Automatic Computation, No. 2, University of California Press, Berkeley, 1970.
- Donchin, E., and Lindsley, D. B. Average evoked potentials and reaction times to visual stimuli. *EEG Clin. Neurophysiol.* 20, 217-223, 1966.
- Galbraith, G. C. Cross-spectral coherence analysis of central nervous system coupling patterns, *Proc. Symp. Biomed. Eng., Marquette University* 1, 341-344, 1966.
- Galbraith, G. C. The effect of prior EEG "coupling" upon the visual evoked response. *IEEE Trans. Biomed. Eng., BME-4* (4), 223-229, 1967.
- Hall, D. J., Ball, G. H., Wolf, D. E., and Eusebio, J. W. PROMENADE-- A system for on-line pattern recognition. *In The Future of Statistics*, Academic Press, New York, 390-413, 1968.
- John, E. R., Ruchkin, D. S., and Villegas, J. Experimental background: signal analysis and behavior correlates of evoked potential configurations in cats. *Ann. N. Y. Acad. Sci.*, 112, 362-420, 1964.
- MacNeilage, P. F., and MacNeilage, L. A. Central processes controlling speech production during sleep and waking. *In Conference on the Psychophysiology of Thinking*, Hollins College, Va., F. J. McGuigan (ed.), October 18-21, 1971.
- McGuigan, F. J. Covert oral behavior during the silent performance of language tasks. *Psych. Bulletin* 74, 309-326, 1970.
- Penfield, W., and Jasper, H. H. *Epilepsy and the Functional Anatomy of the Human Brain*, Little, Brown, Boston, p. 575, 1954.
- Penfield, W., and Roberts, L. *Speech and Brain-Mechanisms*, Princeton University Press, Princeton, 1959.

- Rose, G., and Lindsley, D. B. Visually evoked electrocortical responses in kittens: development of specific and nonspecific systems. *Science* 148, 1244-1246, 1965.
- Selby, S. M. (ed.). *Standard Mathematical Tables*, 19 edition, The Chemical Rubber Co., Cleveland, July 1971.
- Singleton, R. C. On computing the fast Fourier transform. *Commun. of the ACM* 10, 647-654, 1967.
- Van Riper, C., and Irwin, J. V. *Voice and Articulation*, Prentice-Hall, Englewood Cliffs, 1958.
- Walter, D. O. Spectral analysis for electroencephalograms: mathematical determination of neurophysiological relationships from records of limited duration. *Exp. Neurol.* 8, 155-181, 1963.
- Walter, D.O., and Adey, W. R. Analysis of brain-wave generators as multiple statistical time series. *IEEE Trans. Bio-Medical Eng.*, BME-12, 8-13, 1965.
- Watson, J. B. *Behaviorism*, University of Chicago Press, Chicago, 1930.